MEDICAL IMAGING INFORMATICS: LECTURE # 6

SEGMENTATION

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Overview

- Definitions
- Role of Segmentation
- Segmentation methods
  - Intensity based
  - Shape based
  - Texture based
- Summary & Conclusion
- Literature

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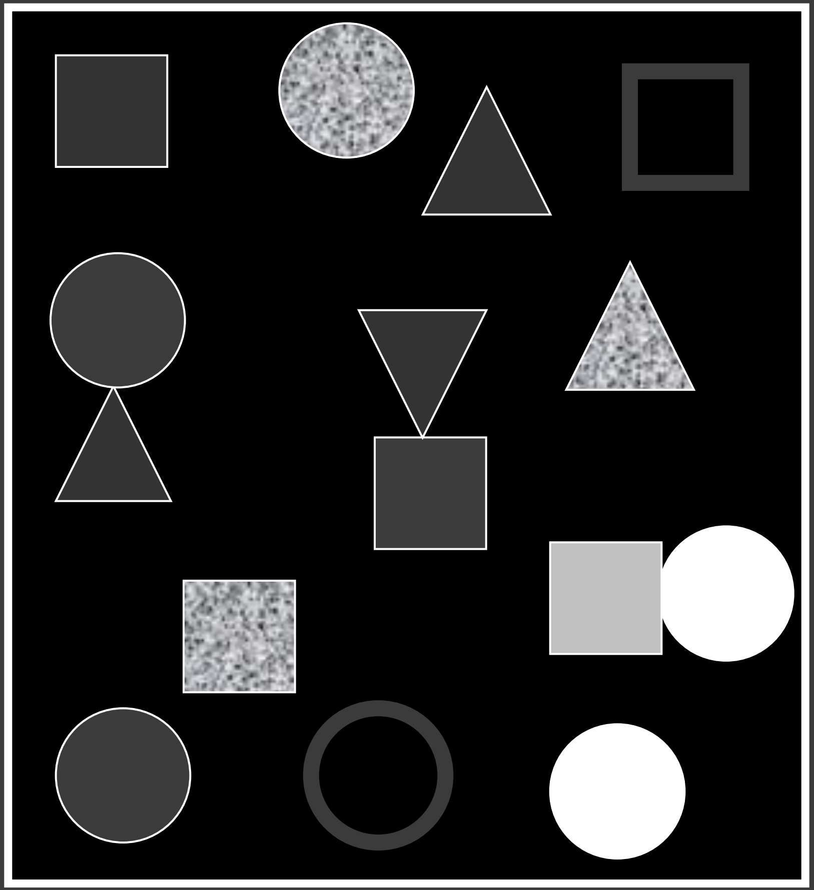
The Concept Of Segmentation

Identify classes (features) that characterize this image!



Intensity: Bright - dark

Shape: Squares , spheres, triangles

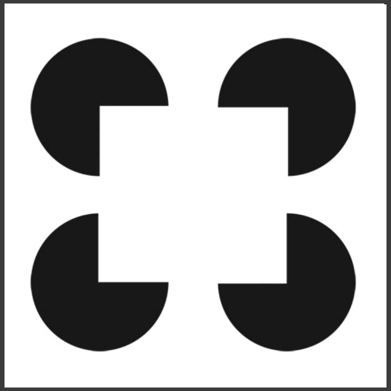
Texture: homogeneous – speckled

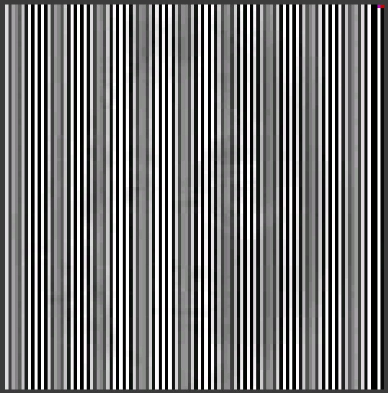
Connectivity: Isolated - connected

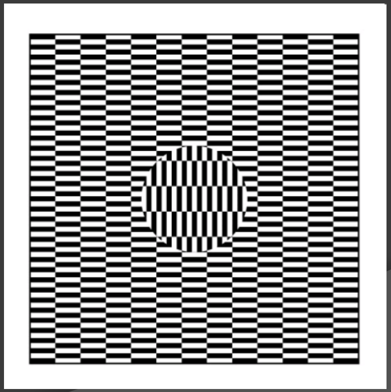
Topology: Closed - open

More On The Concept Of Segmentation:

Deterministic versus probabilistic classes
Can you still identify multiple classes in each image?







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Segmentation Of Scenes

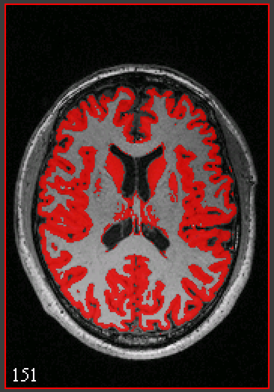
Segment this scene!
Hint: Use color composition and spatial features

By J. Chen and T. Pappas; 2006, SPIE; DOI: 10.1117/2.1200602.0016

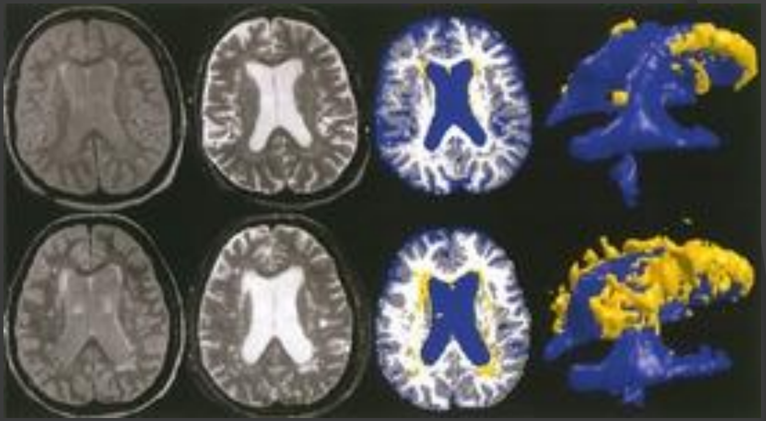
Examples: Intensity, Texture, Topology

By intensity

Gray matter segmentation



topology



By texture

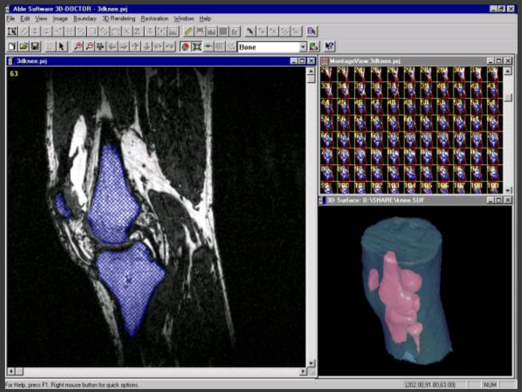
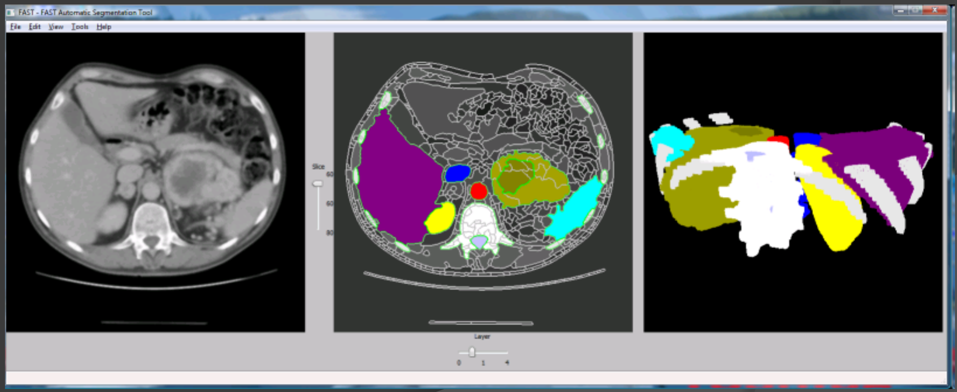


image at: www.ablesw.com/3d-doctor/3dseg.htm

Segmentation of abdominal CT scan



Stephen Cameron. Oxford U, Computing Laboratory

Definitions

- Segmentation is the partitioning of an image into regions that are homogeneous with respect to some characteristics.

In medical context:

- Segmentation is the delineation of anatomical structures and other regions of interest, i.e. lesions, tumors.

Formal Definition

If the domain of an image is Ω, then the segmentation problem is to determine sets (classes) Z_k, whose union represent the entire domain

$$\Omega = \bigcup_{k=1}^{N} Z_k$$

Sets are connected:

$$Z_k \bigcap Z_j = \alpha;$$
$$k \neq j; 0 \leq \alpha < \Omega$$

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More Definitions

- When the constraint of connected regions is removed, then determining the sets Z_k is termed pixel classification.

- Determining the total number of sets K can be a challenging problem.

- In medical imaging, the number of sets is often based on a-priori knowledge of anatomy, e.g. K=3 (gray, white, CSF) for brain imaging.

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Labeling

- Labeling is the process of assigning a meaningful designation to each region or pixel.
- This process is often performed separately from segmentation.
- Generally, computer-automated labeling is desirable
- Labeling and sets Z_k may not necessarily share a one-to-one correspondence

Dimensionality

- Dimensionality refers to whether the segmentation operates in a 2D or 3D domain.
- Generally, 2D methods are applied to 2D images and 3D methods to 3D images.
- In some instances, 2D methods can be applied sequentially to 3D images.

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Characteristic and Membership Functions

- A characteristic function is an indicator whether a pixel at location j belongs to a particular class Z_k.

$$\chi_k\left(j\right) = \begin{cases} 1\, if.element.of.class \\ 0 \quad\quad otherwise \end{cases}$$

- This can be generalized to a membership function, which does not have to be binary valued.

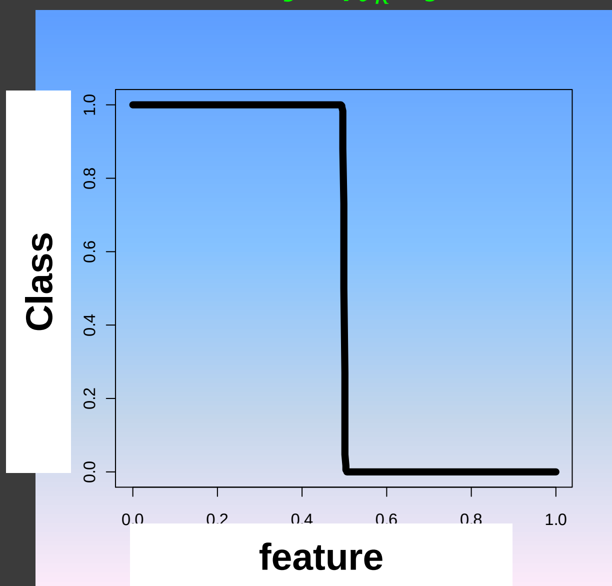
$$0 \le \chi_k\left(j\right) \le 1,\ for.all.pixels.\&.classes$$

$$\sum_{k=1}^{N} \chi_k\left(j\right) = 1,\ for.all.pixels$$

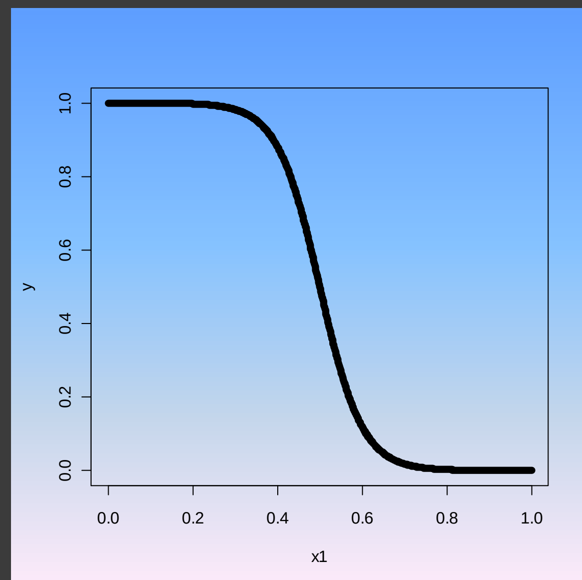
- The characteristic function describes a “deterministic” segmentation process whereas the membership function describes a “probabilistic” one.

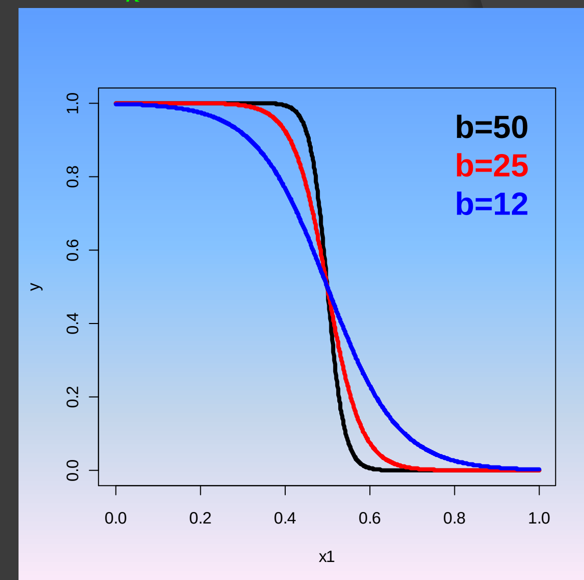
Simple Membership Functions

$binary : \chi_k \quad j$



$probabilistic : \chi_k \quad j$





$sigmoid.function$

$$y = \frac{1}{1+\exp\left(-\left(a-x\right)*b\right)}$$

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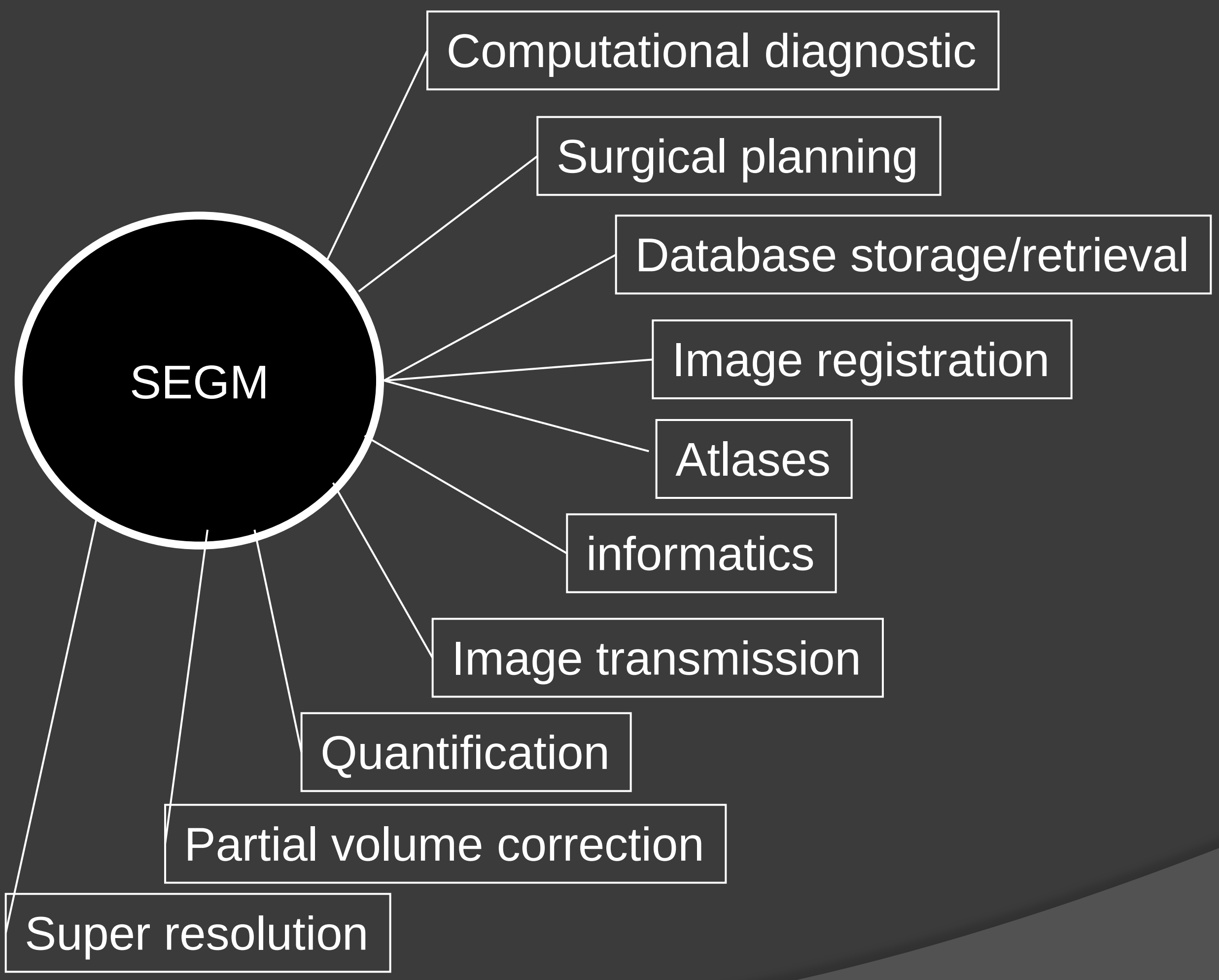
Segmentation Has An Important Role



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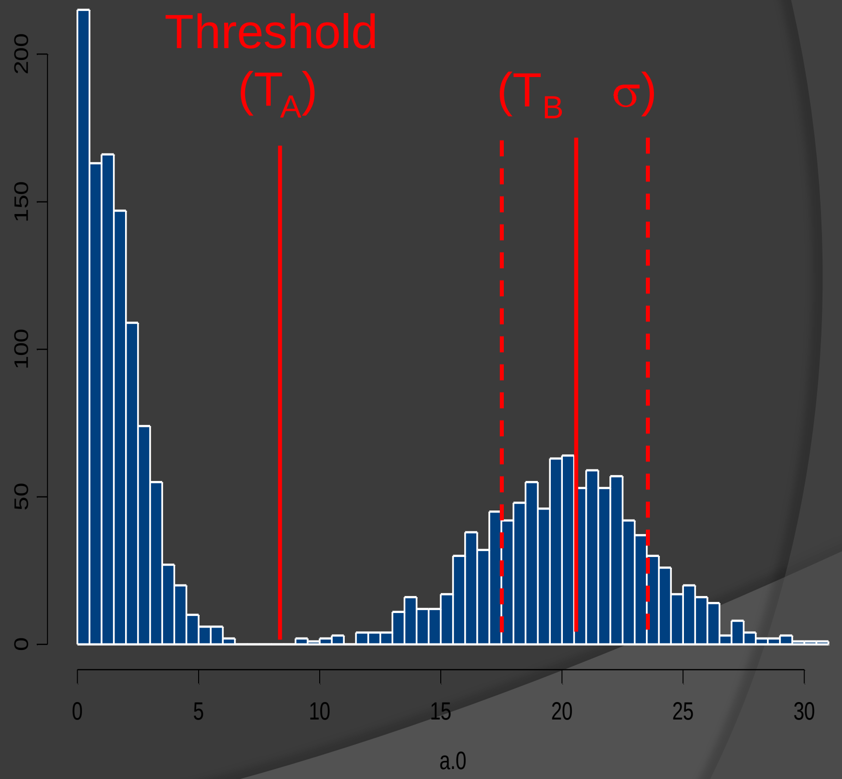
Segmentation Methods

Threshold Method

Angiogram showing a right MCA aneurysm

Dr. Chris Ekong;
www.medi-fax.com/atlas/brainaneurysms/case15.htm

Histogram (fictitious)



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Threshold Method

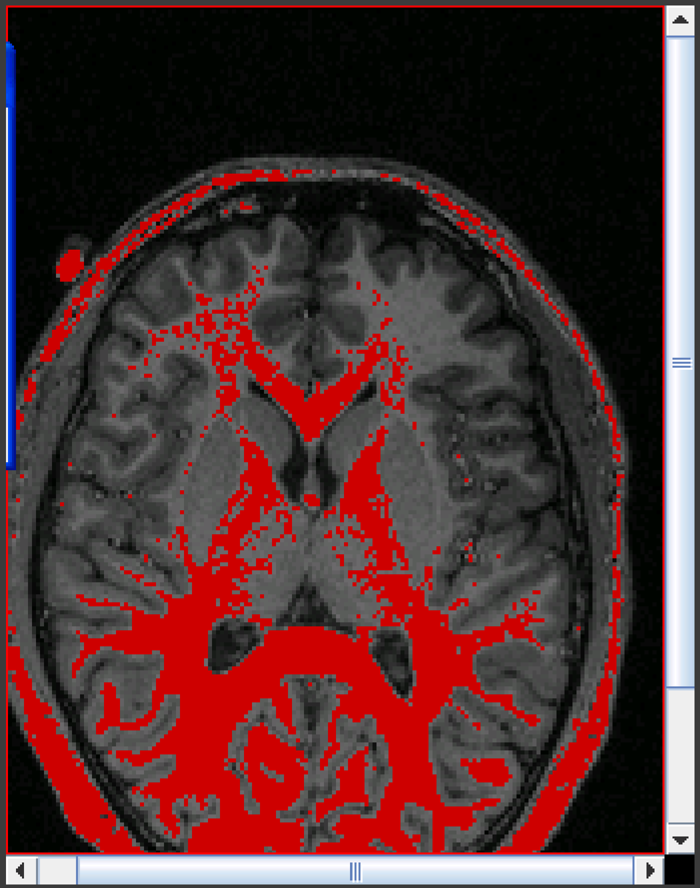
Original

Threshold min/max

Threshold standard deviation

Threshold Method Applied To Brain MRI

White matter segmentation



- •Major failures:
    - •Anatomically non-specific
    - •Insensitive to global signal inhomogeneity

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Threshold: Principle Limitations

- Works only for segmentation based on intensities
- Robust only for images with global uniformity and high contrast to noise
- Local variability causes distortions
- Intrinsic assumption is made that the probability of features is uniformly distributed

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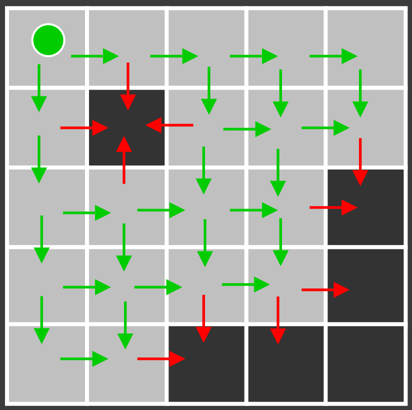
Region Growing - Edge Detection

Seed point

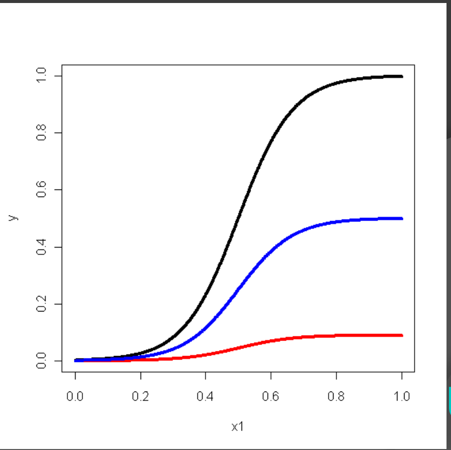


- Region growing groups pixels or subregions into larger regions.
- A simple procedure is pixel aggregation,
- It starts with a "seed" point and progresses to neighboring pixels that have similar properties.
- Region growing is better than edge detection in noisy images.

Guided e.g. by energy potentials:

Similarity: $$V(i,j) = \frac{I_i - I_j}{\sigma_{i,j}}, equivalent.to.a.z - score$$

Edges: $$V(l,r) = (I_l - I_r) \cdot erf(x) + I_r$$



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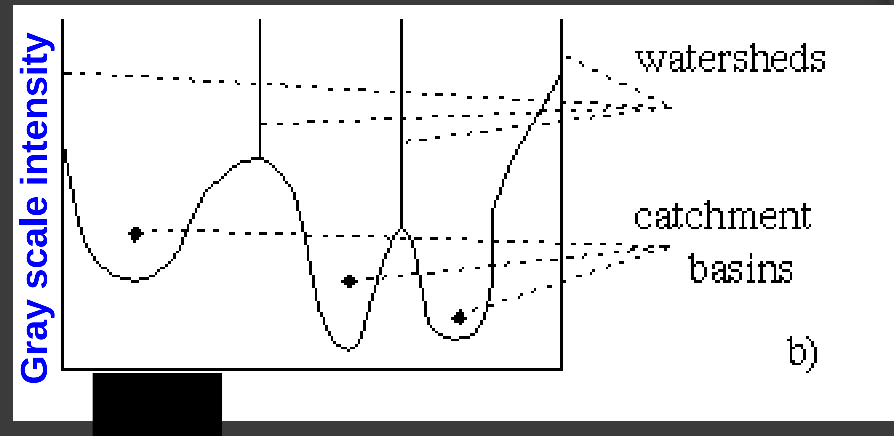
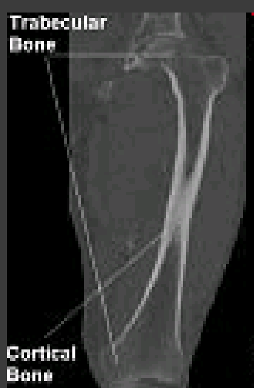
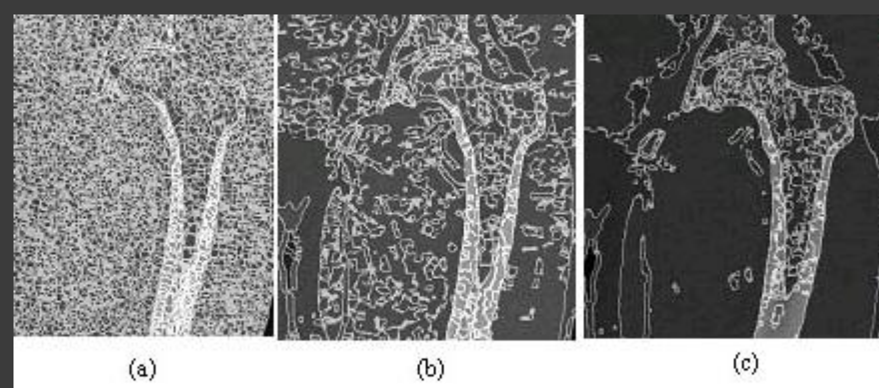
Region Growing – Watershed Technique



(a) WS over-segmentation
(b) WS conditioned by regional density mean values
(c) WS conditioned by hierarchical ordering of regional density mean values

CT of different types of bone tissue (femur area)





M. Straka, et al. Proceedings of MIT 2003

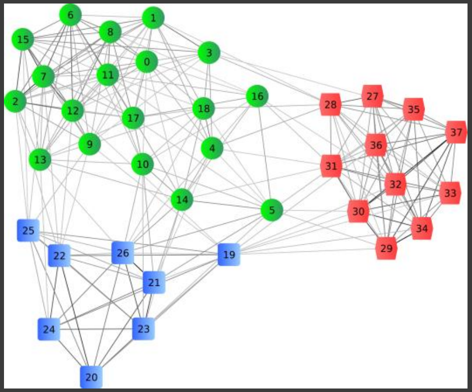
Region Growing: Principle Limitations

- Segmentation results dependent on seed selection
- Local variability dominates the growth process
- Global features are ignored

- Generalization needed:
  - Unsupervised segmentation (i.e.insensitive to selection of seeds)
  - Exploitation of both local and global variability

Clustering

- Generalization using clustering
- Two commonly used clustering algorithms
  - K-mean
  - Fuzzy C-mean



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Definitions: Clustering

- Clustering is a process for classifying patterns in such a way that the samples within a class Z_k are more similar to one another than samples belonging to the other classes Z_m, $m \neq k$; $m = 1 \ldots K$.

- The ***k*-means algorithm** attempts to cluster *n* patterns based on attributes (e.g. intensity) into *k* classes $k < n$.
- The objective is to minimize total intra-cluster variance in the least-square sense:

$$\sigma = \sum_{k=1}^{K} \sum_{\chi_j \in S_k} \chi_j - \mu_k^{\quad 2}$$

- *for k* clusters Z_k, $k = 1, 2, \ldots, K$. μ_i is the mean point (centroid) of all pattern values ♍$_j \in Z_k$.

Fuzzy Clustering

- The ***fuzzy C-means algorithm*** is a generalization of K-means.
- Rather than assigning a pattern to only one class, the ***fuzzy C-means*** assigns the pattern a number m, *0* <= *m* <= *1,* described as membership function.

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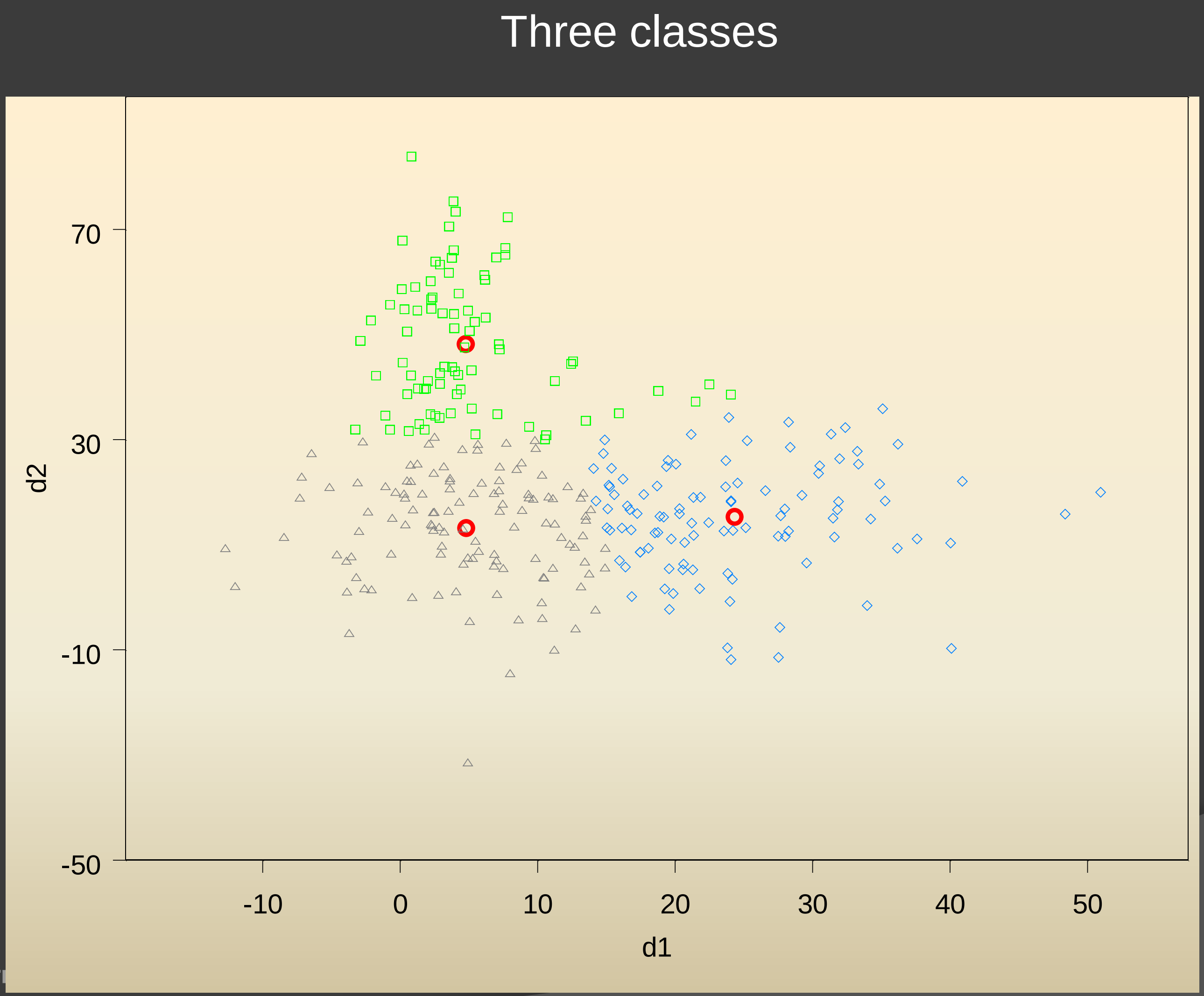
K- means



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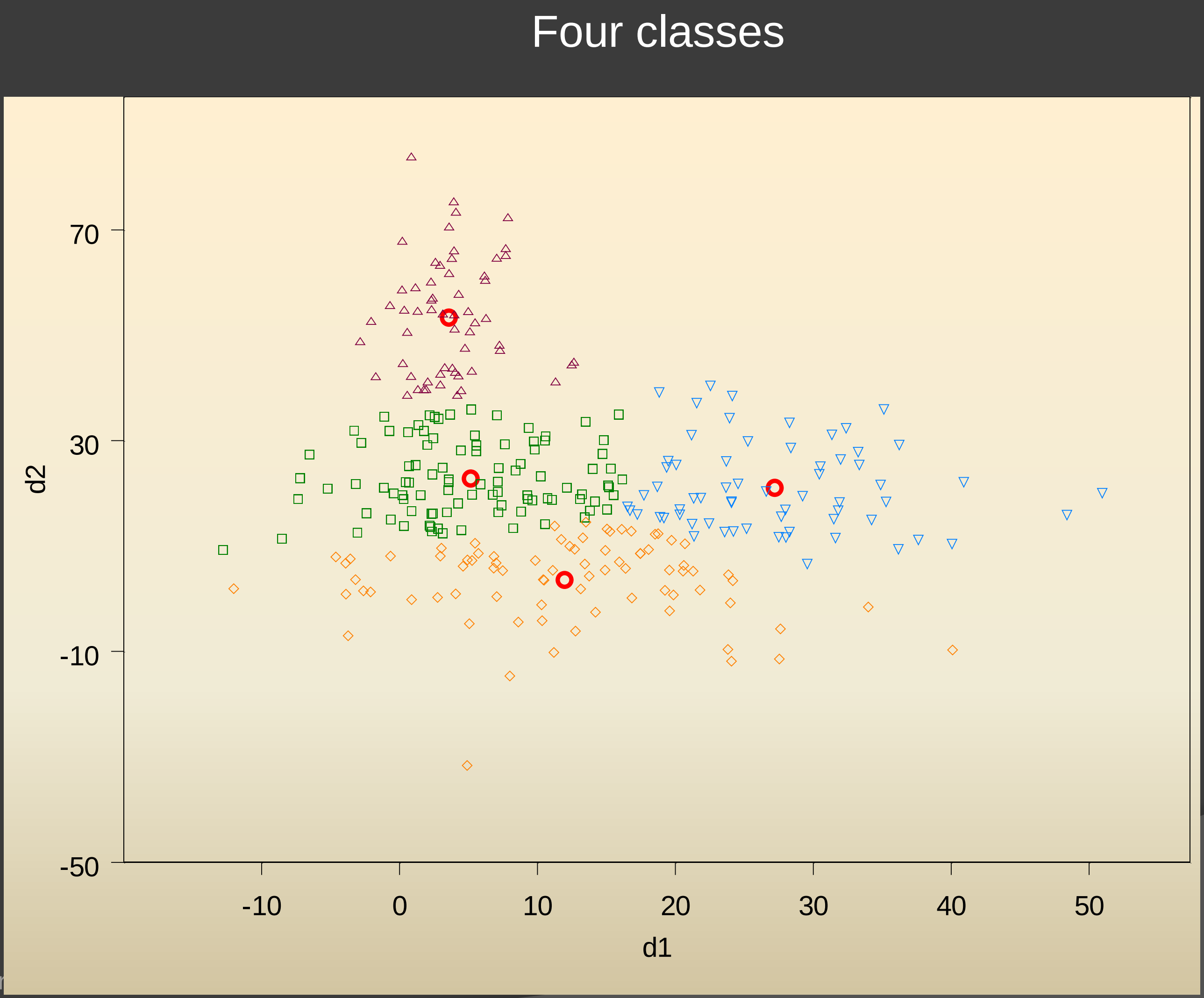
K - means



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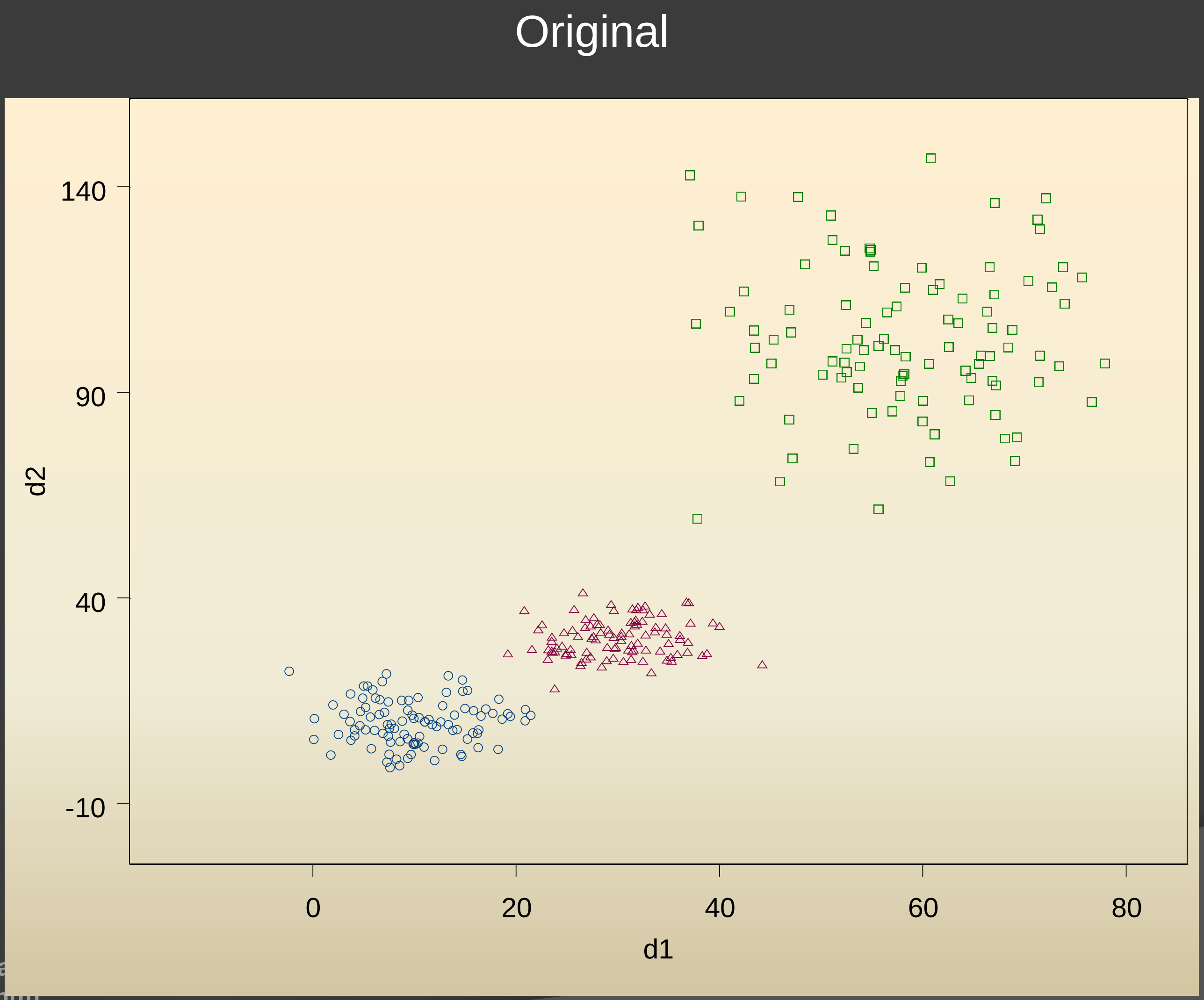
K - means



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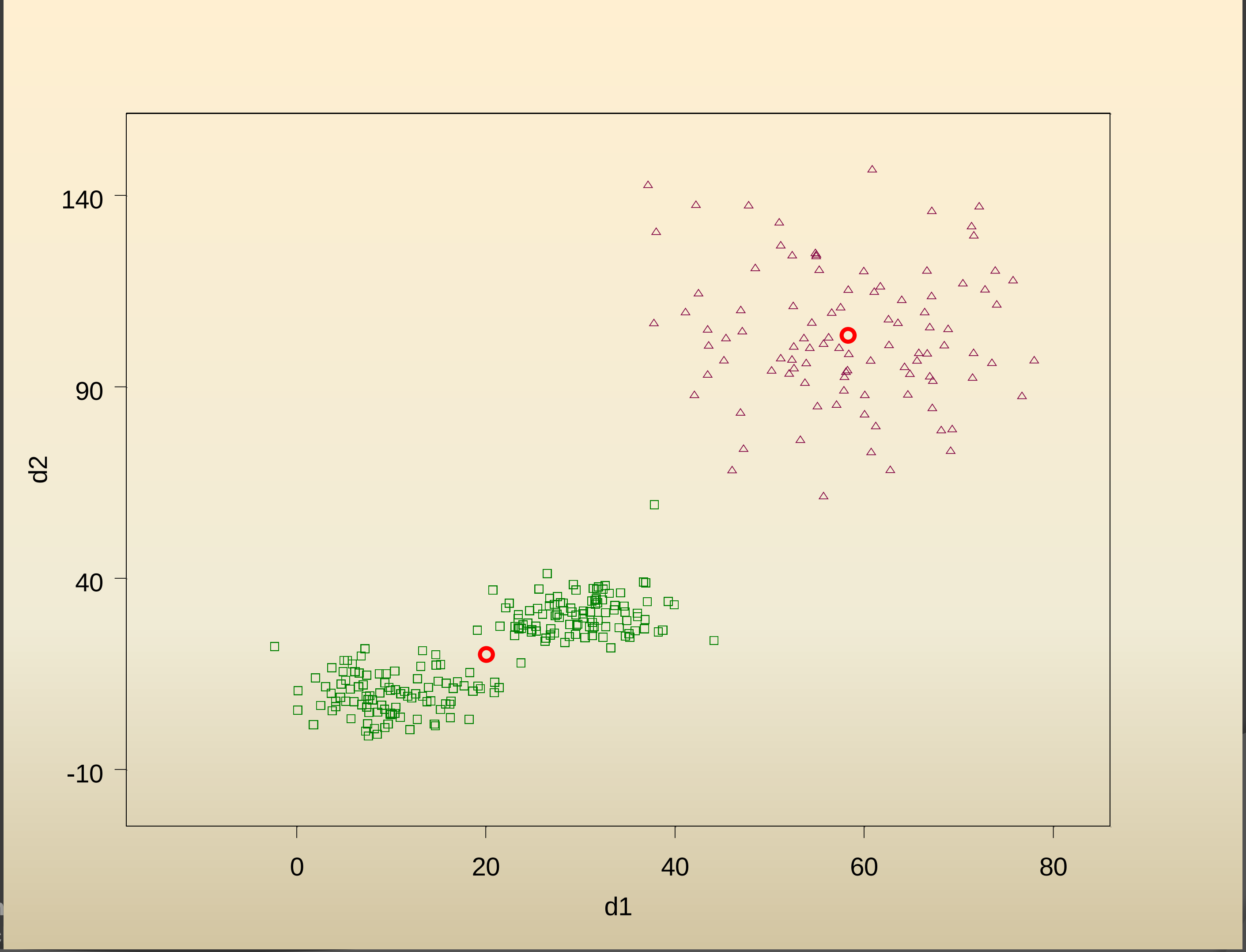
K - means



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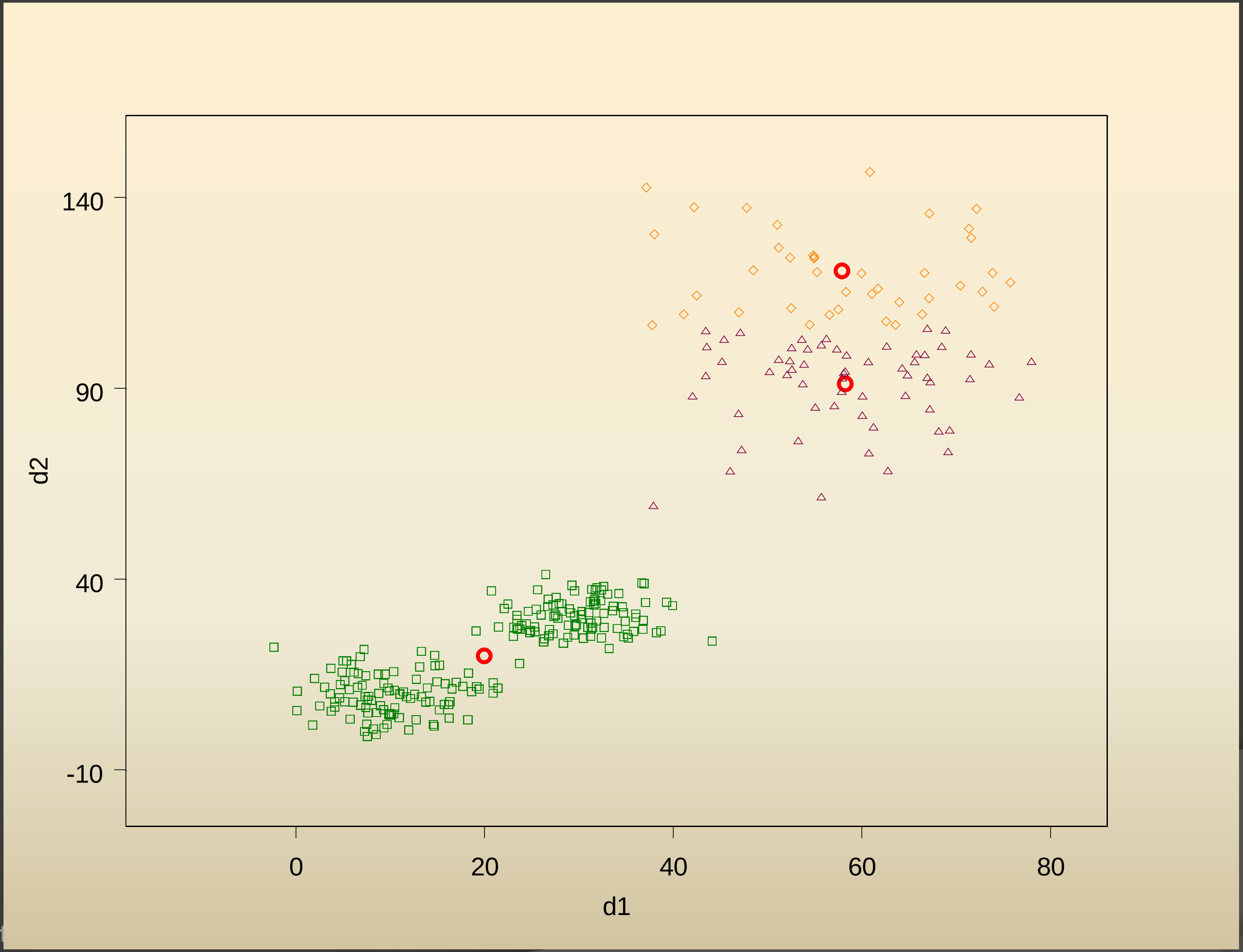
K - means



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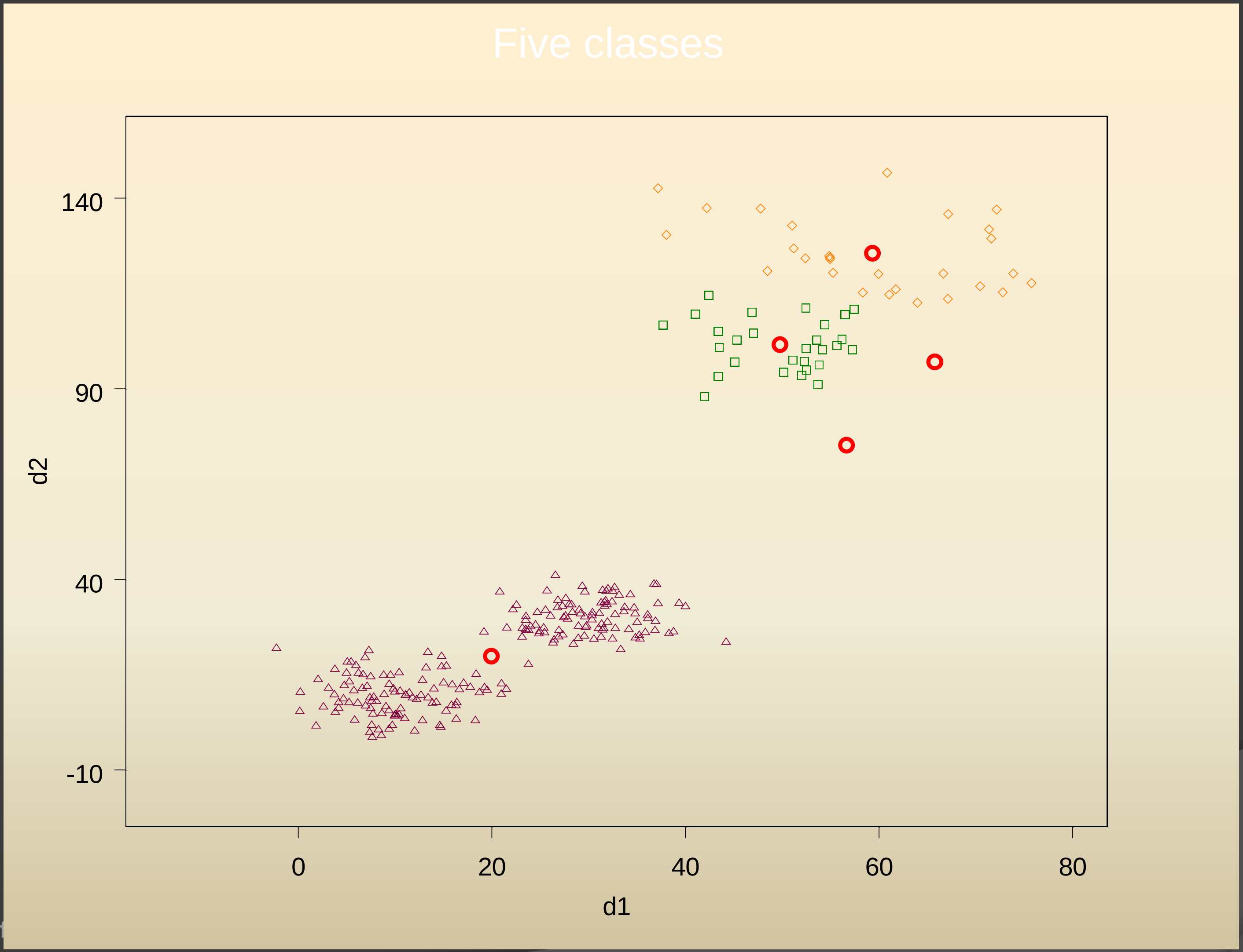
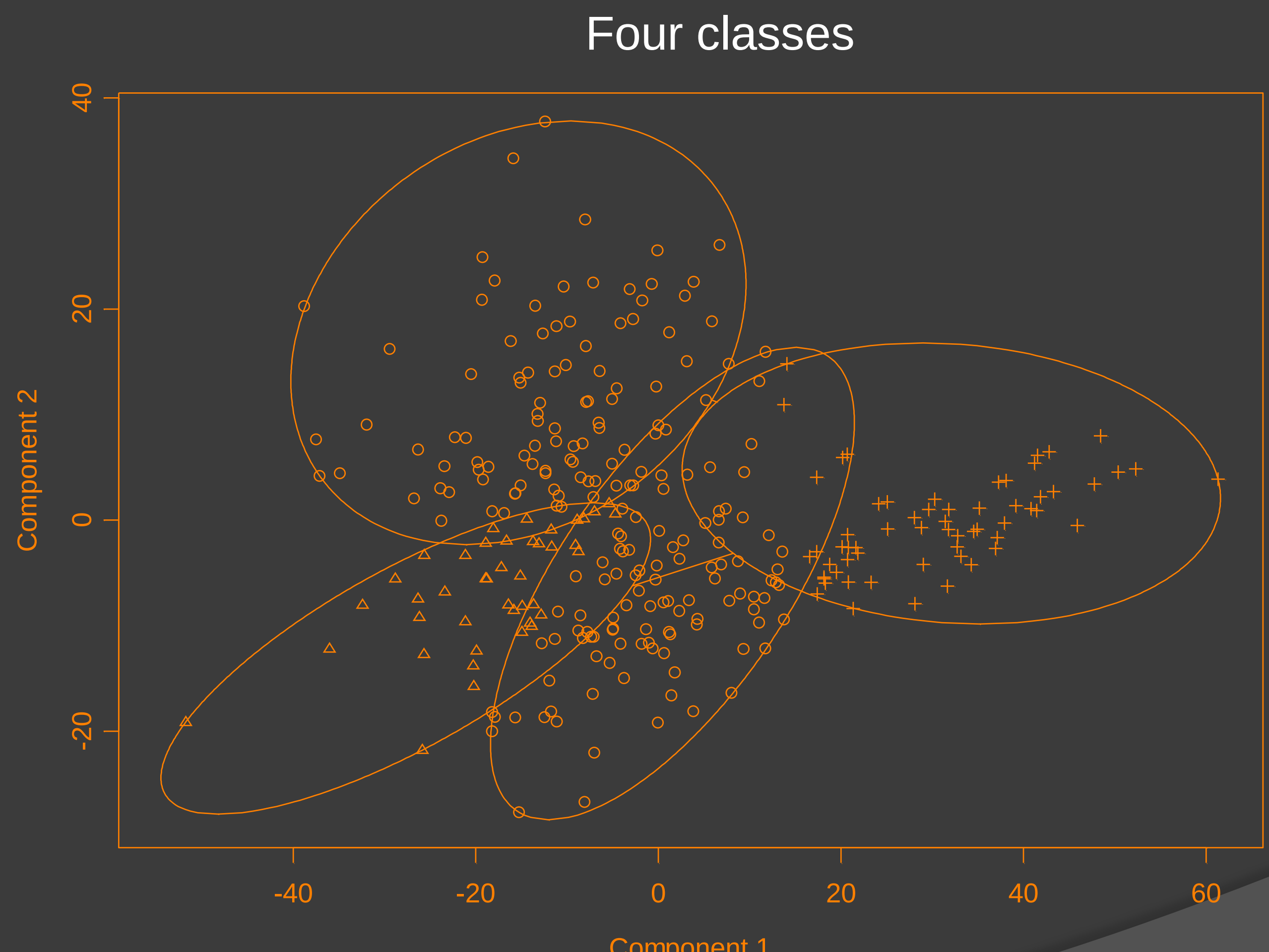
K – means: TRAPPED!



Fuzzy C - means

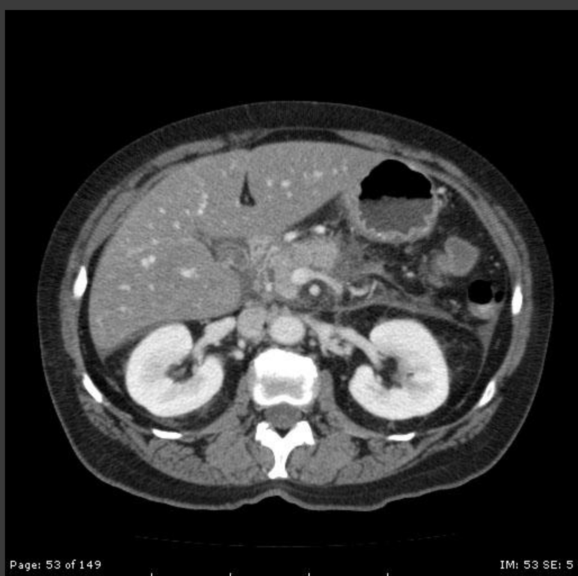


These two components explain 100 % of the point variability.

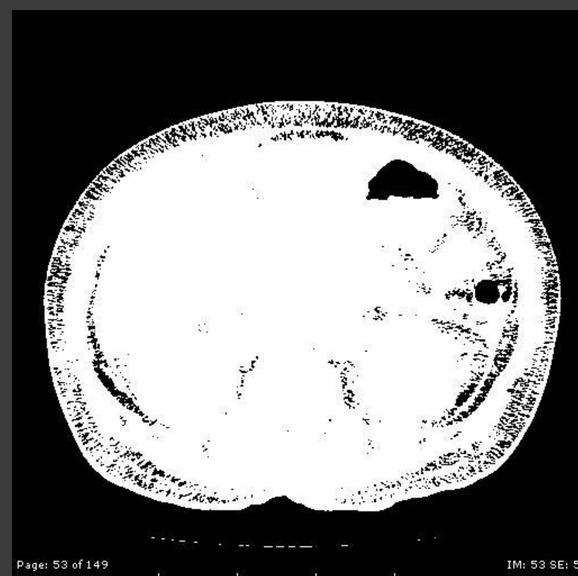
Fuzzy C- Means Segmentation I

Two classes

Original



Class I

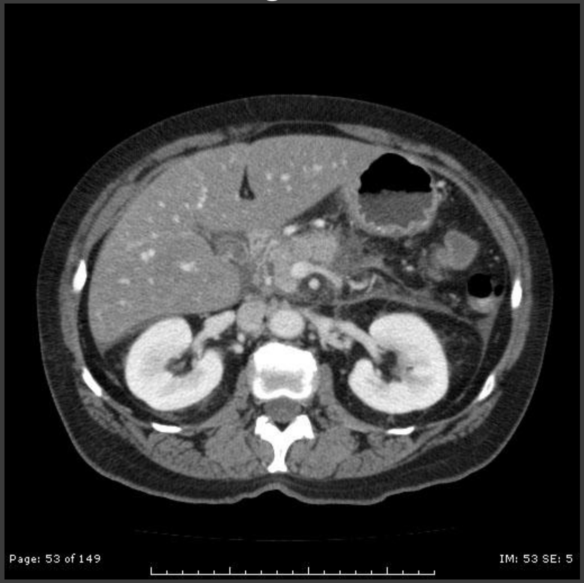


Class 2

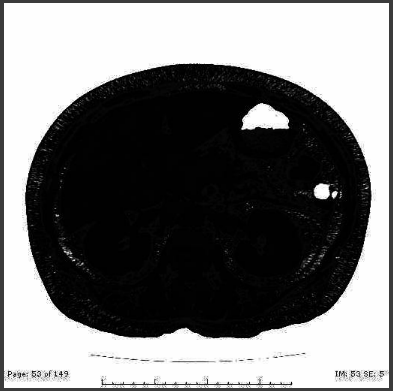
Fuzzy Segmentation II

Four classes

Original



Class I

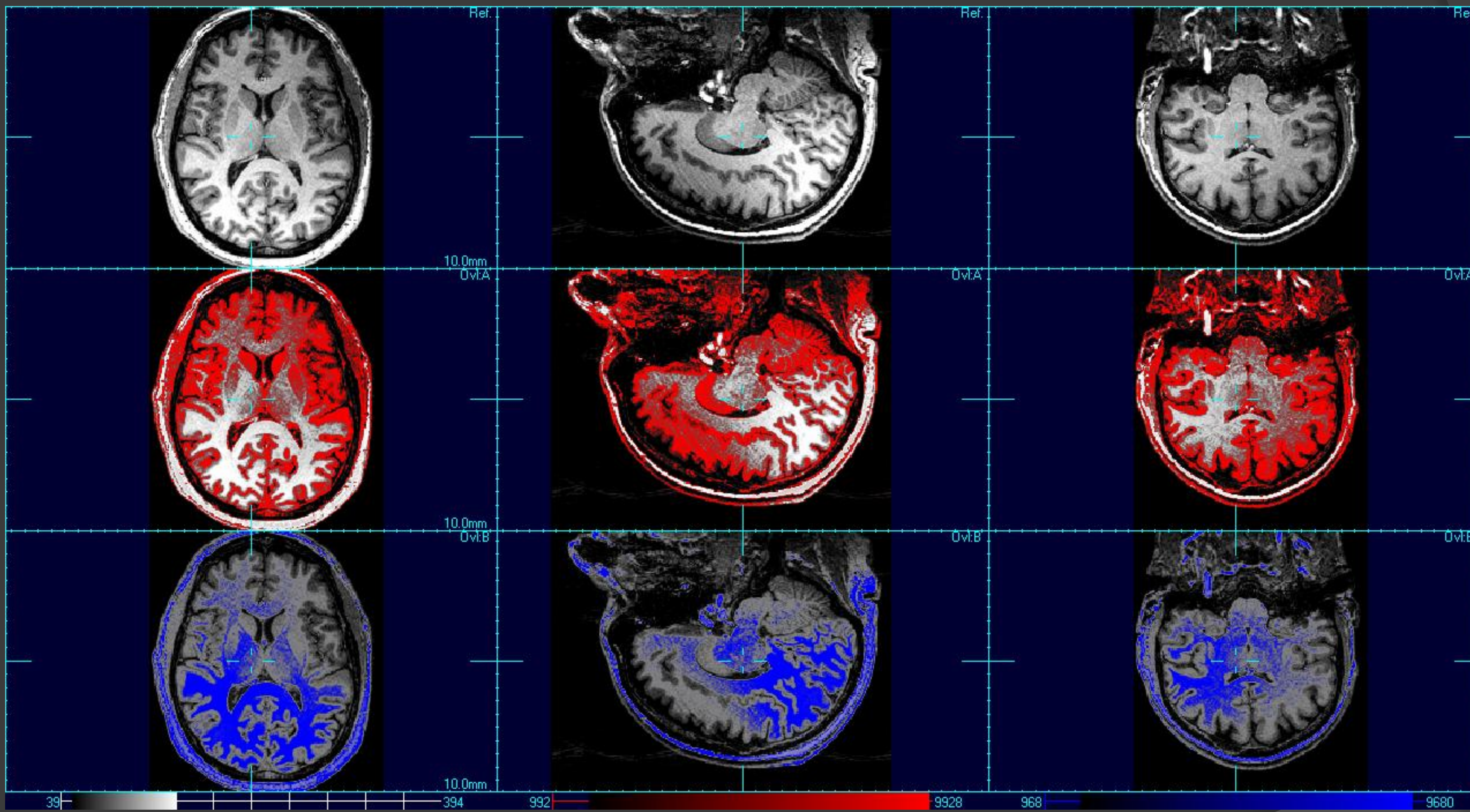


Class 2

Class 3

Class 4

Brain Segmentation With Fuzzy C-Means



4T MRI, bias field inhomogeneity contributes to the problem of poor segmentation

Clustering: Principle Limitations

- Convergence to the optimal configuration is not guaranteed.
- Outcome depends on the number of clusters chosen.
- No easy control over balancing global and local variability
- Intrinsic assumption of a uniform feature probability is still being made

- Generalization needed:
  - Relax requirement to predetermine number of classes
  - Balance influence of global and local variability
  - Possibility to including a-priori information, such as non-uniform distribution of features.

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Segmentation As Probabilistic Problem

- Treat both intensities **Y** and classes **Z** as random distributions
- The segmentation problems is to find the classes that maximize the likelihood to represent the image

- Segmentation in Bayesian formulation becomes :

$$P(Z\,|\,Y) = \frac{P(Y\,|\,Z) * P(Z)}{P(Y)}$$

- where
  - Z is the segmented image (classes z_1 ….z_K)
  - Y is the observed image (values y_1 ….y_n)
  - p(Z) is the prior probability
  - p(Y|Z) is the likelihood
  - P(Z|Y) is the segmentation that best represents the observation

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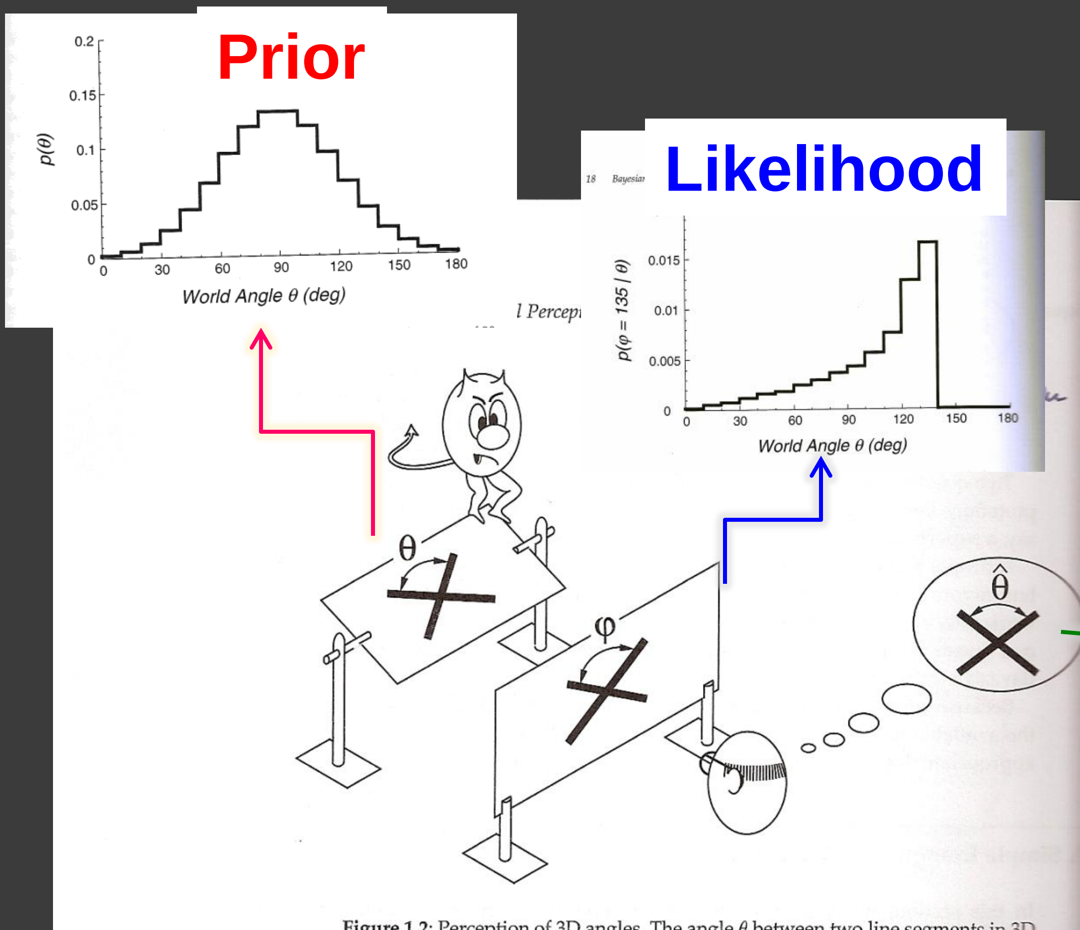
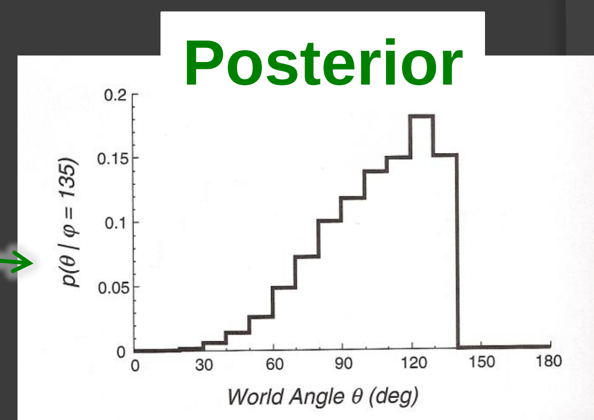
Bayesian Concept

$$p(Z|Y) \propto p(Y|Z) * p(Z)$$





Treat Segmentation As Energy Minimization Problem

- Since p(B) = observation is stable, it follows:

$$\ln\ p(Z\,|\,Y) = \ln\ p(Y\,|\,Z) + \ln\ p(Z)$$

- The goal is to find the most probably distribution of p(Z|Y) given the observation p(Y)
- Since the log probabilities are all additive, they are equivalent to distribution of energy
- segmentation becomes an ***energy minimization problem***.

Probability In Spatial Context

- Use the concept of Markov Random Fields (MRF) for segmentation

- Definition:
  - Classes Z are a MRF
    - Classes exist: p(z) > 0 for all z ♏ Z
    - Probability of z at a location depends only on neighbors
    - Observed intensities are a random process following a distribution of many degrees of freedom.

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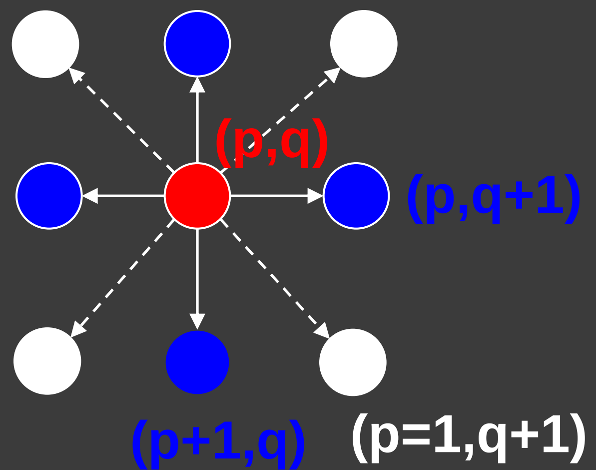
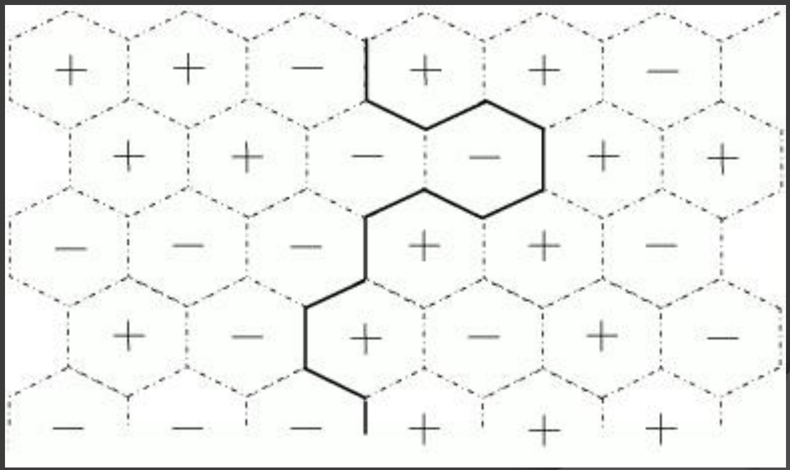
MRF Based Segmentation

1st and 2nd order MRFs

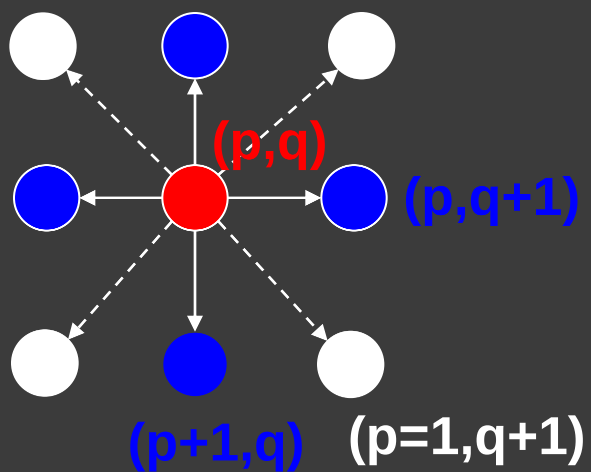


Ising model of spin glasses



MRF Based Segmentation

1st and 2nd order MRFs



- Step I: Define prior class distribution energy:

$$\delta(z_s, z_t) = \begin{cases} -1, & z_s = z_t \\ +1 & z_s \neq z_t \end{cases}$$

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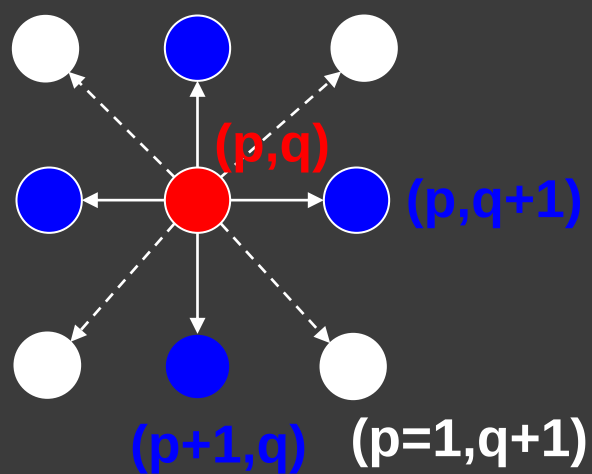
MRF Based Segmentation

1st and 2nd order MRFs



- Step I: Define prior class distribution energy:

$$\delta(z_s, z_t) = \begin{cases} -1, & z_s = z_t \\ +1 & z_s \neq z_t \end{cases}$$

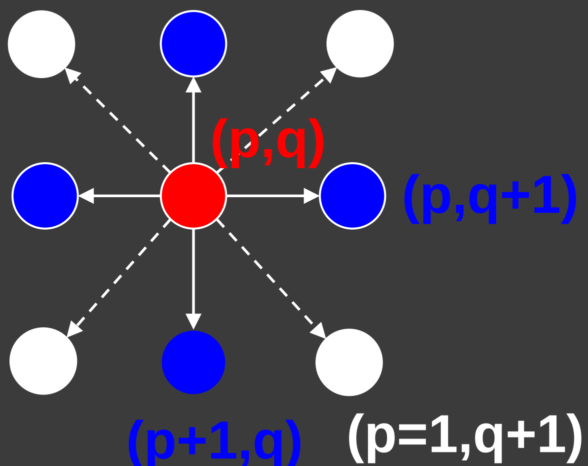
- Step II: Select distribution of conditional observation probability, e.g gaussian:

$$E_{y|z}(p,q) \propto \frac{(y_{p,q} - \mu_z)^2}{2\sigma_z^2}.$$

  - $Y_{p,q}$ is the pixel value at location (p,q)
  - μ_z and σ_z are the mean value and variance of the class z

MRF Based Segmentation

1st and 2nd order MRFs



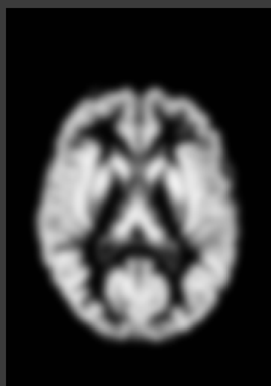
Step III: Solve (iteratively) for the minimal distribution energy

$$\arg\min E_{z|y}(p,q) \propto \underbrace{\sum_{t\in N_s} \delta(z_s, z_t)}_{\text{assignment}} + \underbrace{\frac{\left(y_{p.q} - \mu_z\right)^2}{2\sigma_z^2}}_{\text{similarity}}$$

energy

How To Obtain A Prior Of Class Distributions?

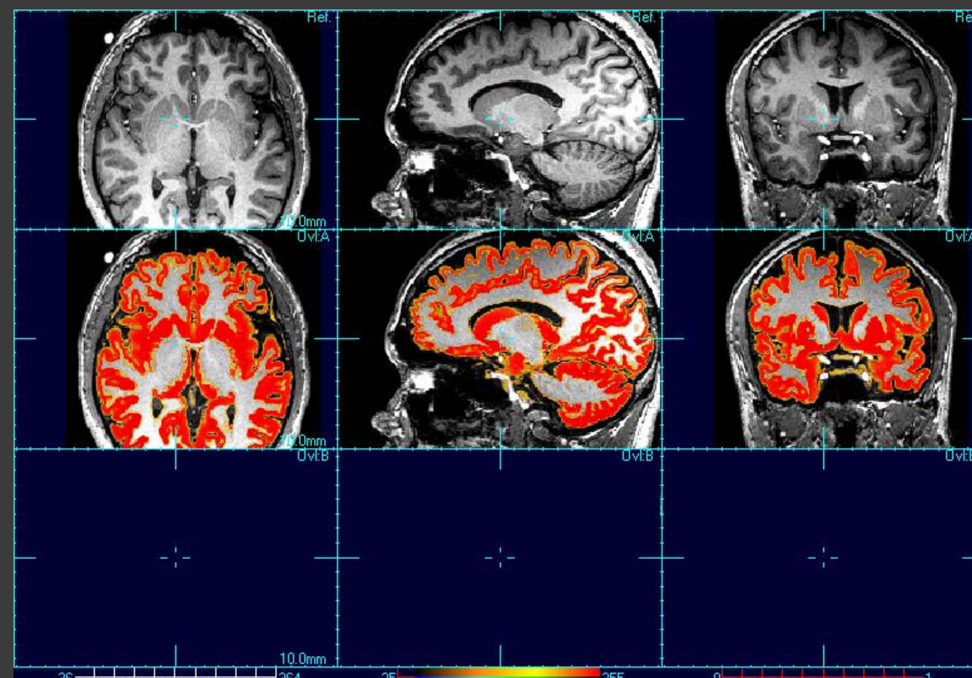
Average Gray Matter Map
Of 40 Subjects



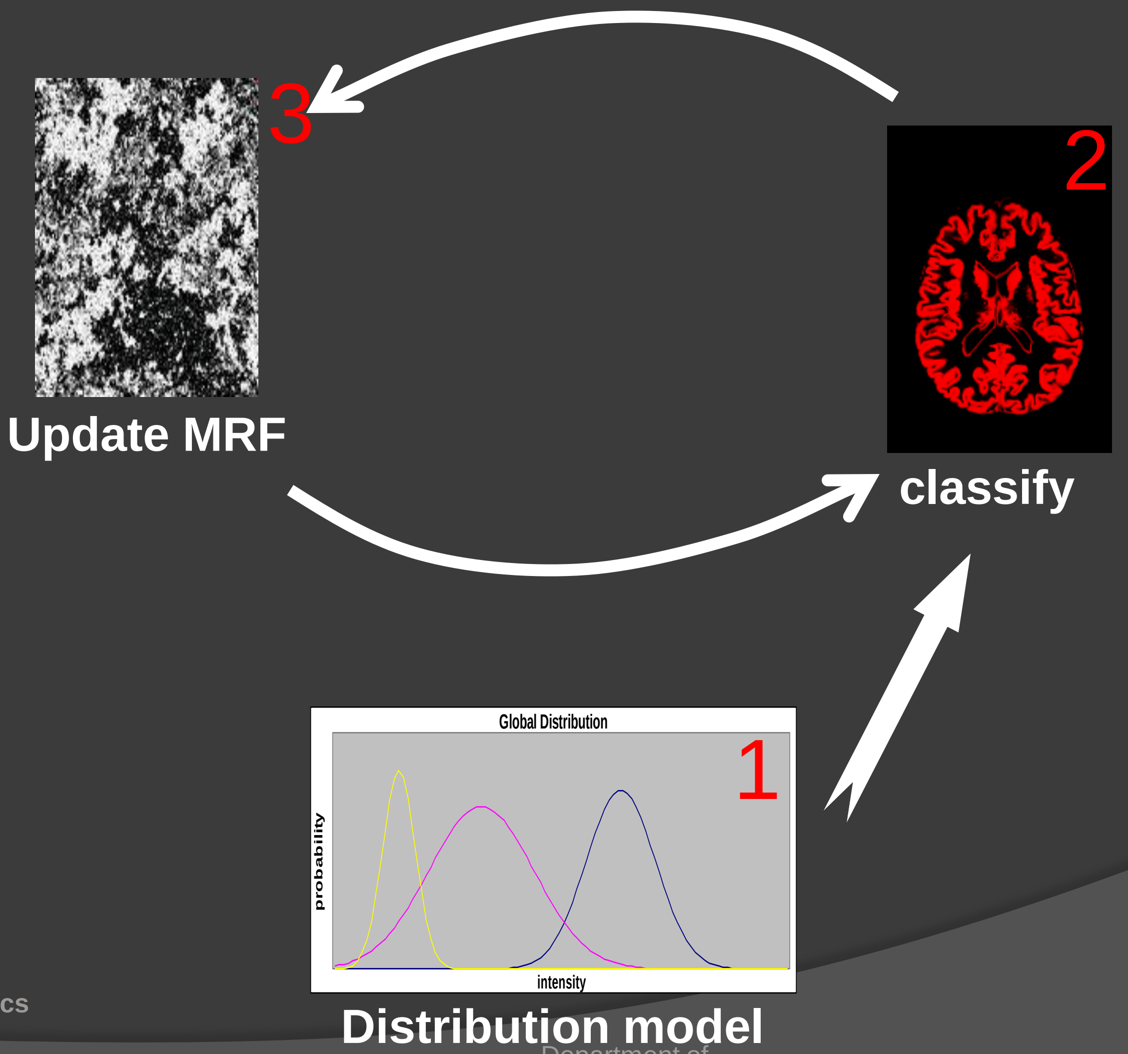
Register to

Segment

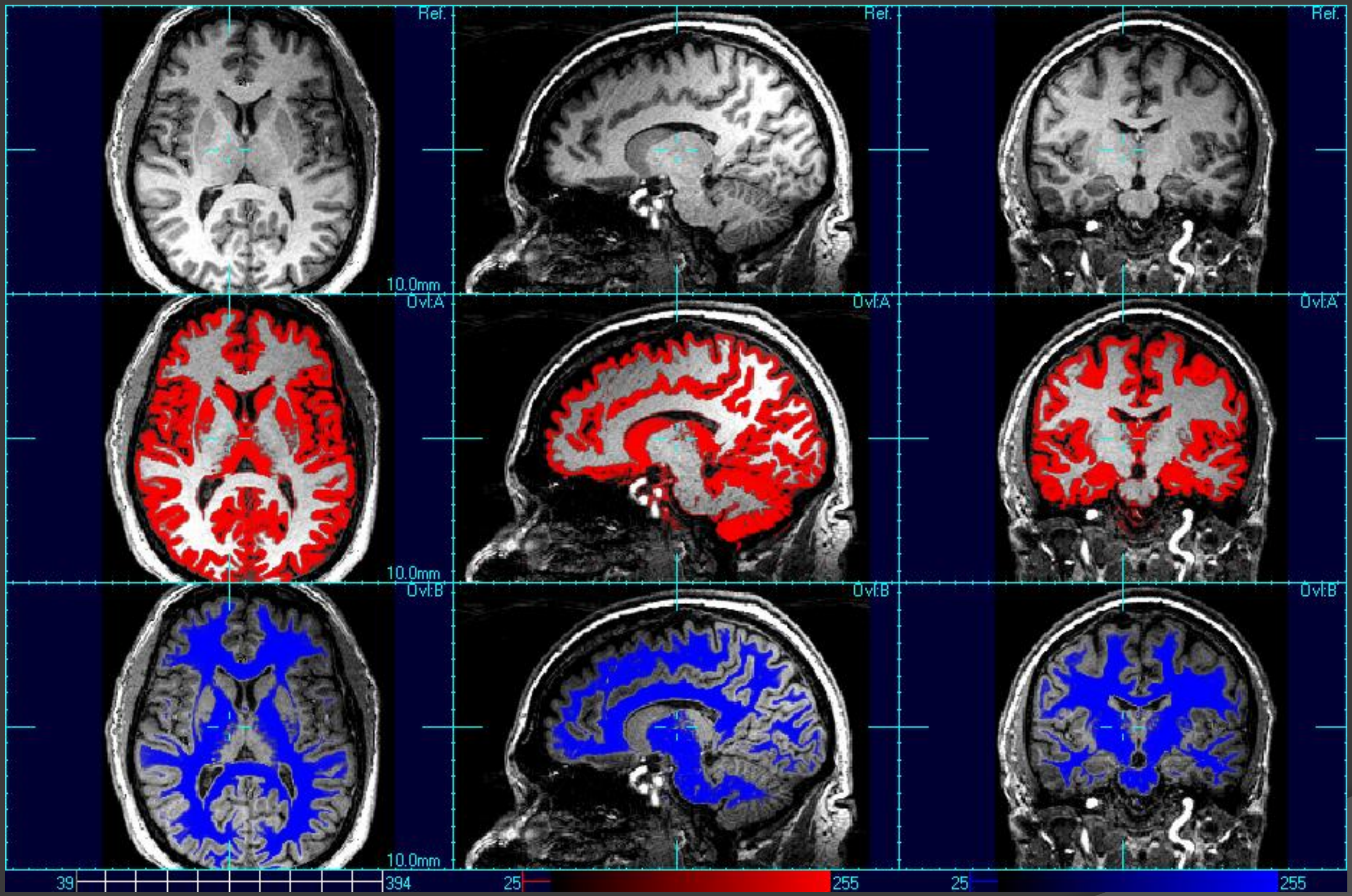
Individual MRI



The Process of MRF Based Segmentation



MRF Based Segmentations



4T MRI, SPM2, priors for GM, WM based on 60 subjects

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Generalization:
Mixed Gaussian Distributions

White matter

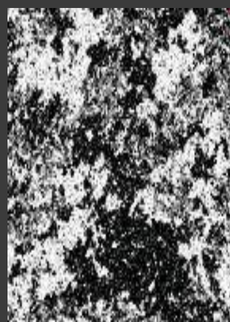
$$\arg\min E_{z|y}(p,q) \propto \sum_{t \in N_s} \delta(z_s, z_t) + \frac{(y_{p.q} - \mu_z)^2}{2\sigma_z^2}.$$

White matter White matter lesion

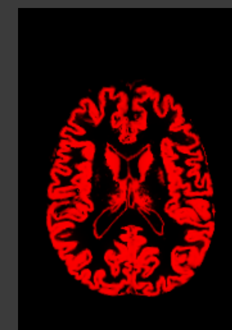
$$\arg\min E_{z|y}(p,q) \propto \sum_{t \in N_s} \delta(z_s, z_t) + \frac{(y_{p.q} - \mu_z)^2}{2\sigma_z^2} + \frac{(y_{p.q} - \mu_w)^2}{2\sigma_w^2} + .$$

Find solution iteratively using
Expectation Maximization (EM)

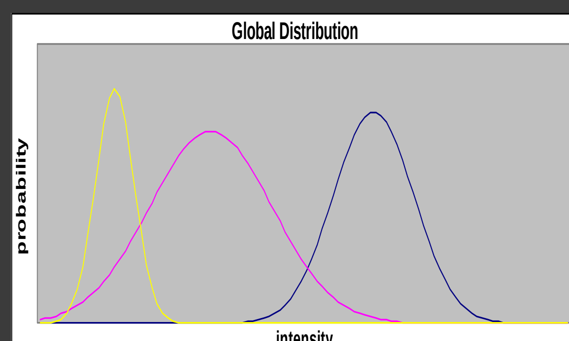
Expectation Maximization Of MRF Based Segmentation



UpdateMRF



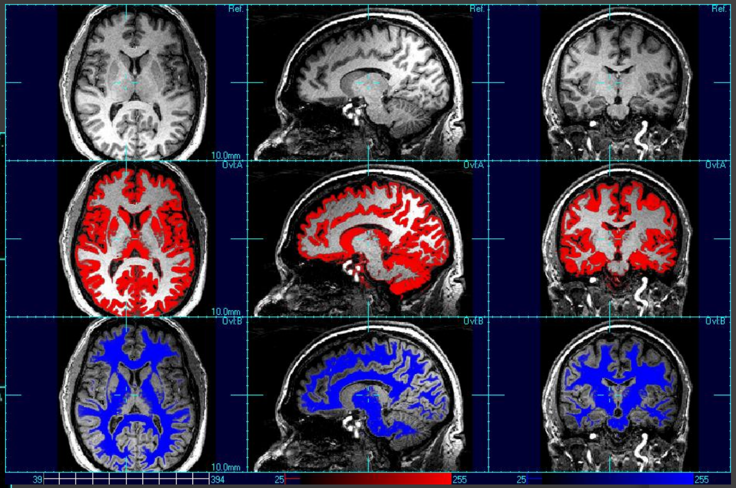
classify

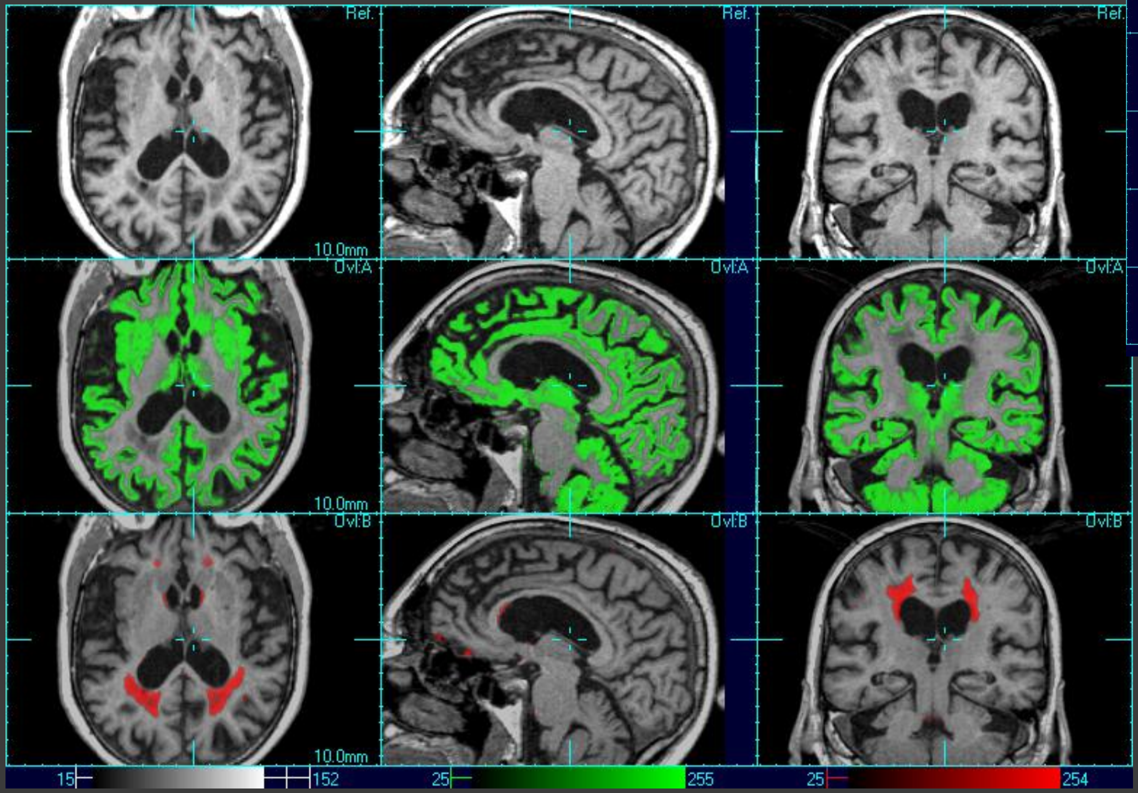


Update distribution model

EMS

Standard





1.5 MRI, SPM2, tissue classes: GM, WM, CSF, WM Lesions

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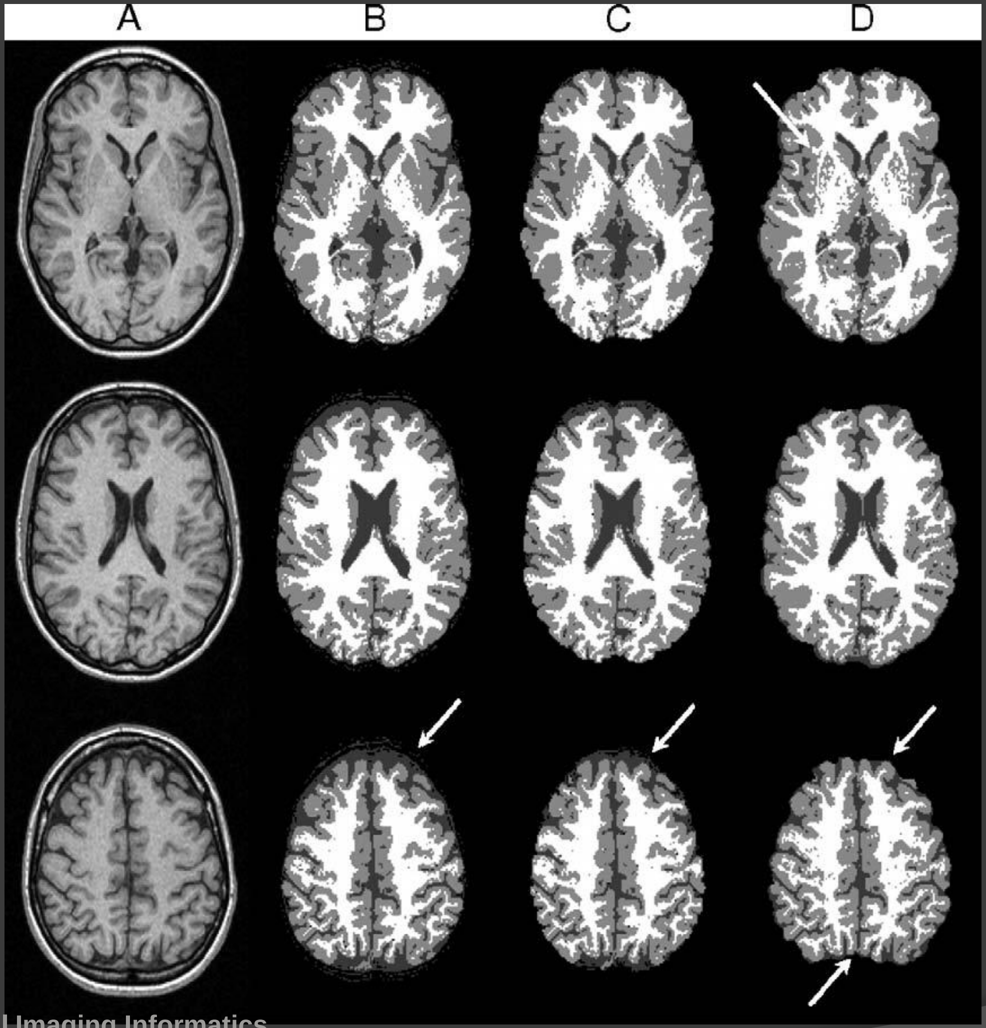
MRF Based Segmentation Using Various Methods



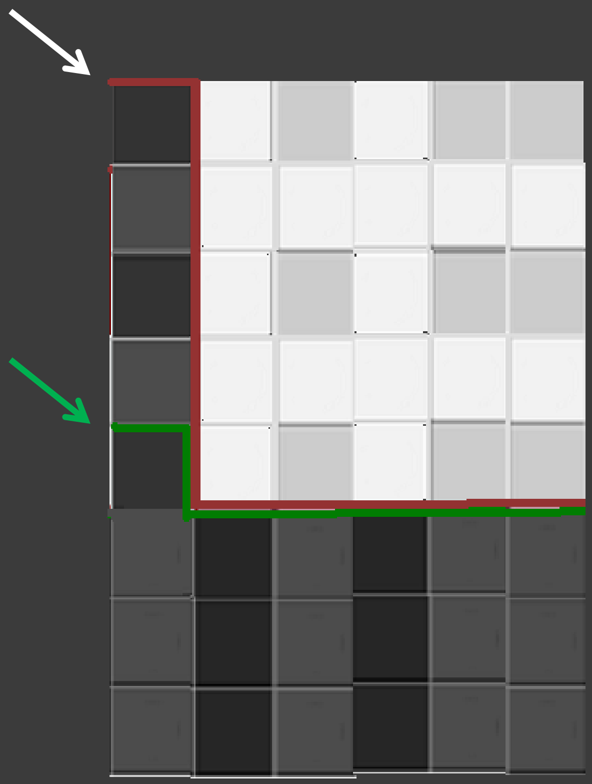
A: Raw MRI
B: SPM2
C: EMS
D: HBSA

from
Habib Zaidi, et al,
NeuroImage 32
(2006) 1591 – 1607

Jie Zhu and Ramin Zabih
Cornell University

GEO-CUTS ALGORITHM FOR 3D BRAIN MRI SEGMENTATION

Principle Limitations Of MRF



Case where a simple energy minimization might not work:

- green: wrong segmentation
- red: correct segmentation

The segmentation energy of green might be smaller than that of red based on simple separation energy

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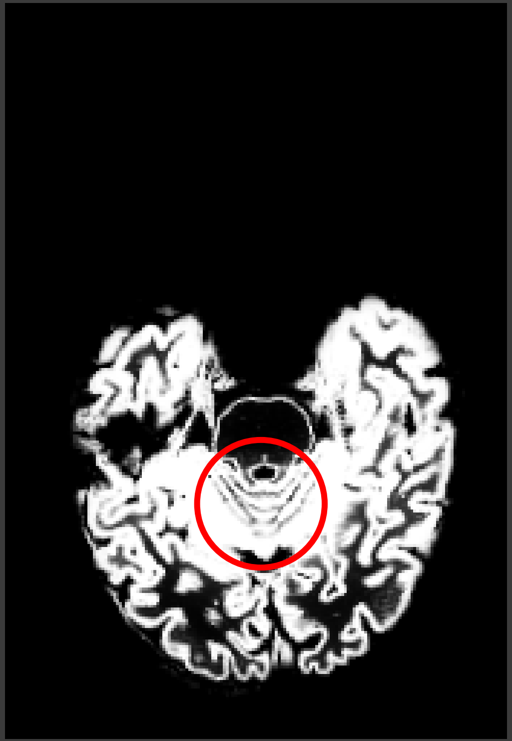
A Case As Motivation

- EMS

EMS gray matter segmentation



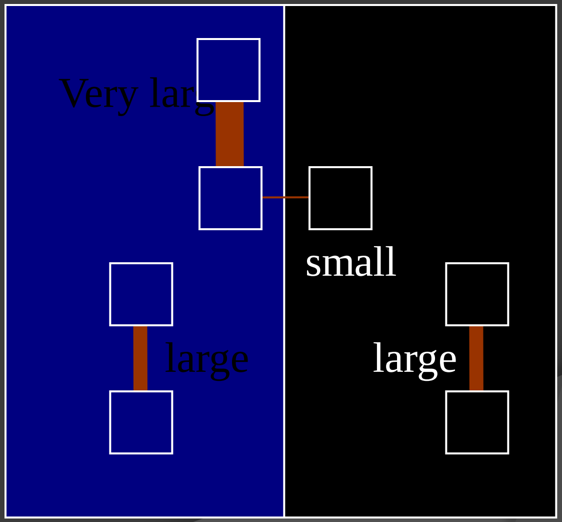
- areas where EMS have problems.

How Geo-cuts Works

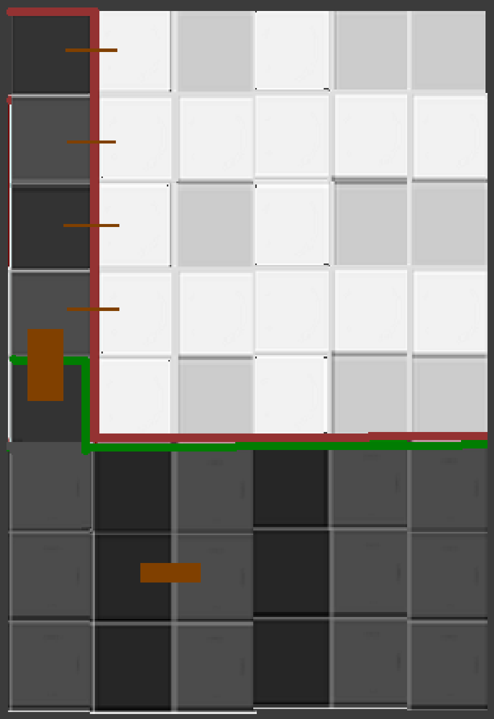
- The separation penalty is defined based on magnitude and direction of image gradient:
  - Small gradient magnitude:
    - separation penalty: large (all directions)

$$E\ \ p,q\ = \frac{1}{\nabla\ \ I_p - I_q}$$

  - Large gradient magnitude
    - separation penalty :
      - small in direction of gradient.
      - very large in other directions.



Why Use Geo Cuts



Case where simple separation energy did not work:

- green: wrong segmentation
- red: correct segmentation

Using Geo-cuts leads to

- Higher separation energy for green *than for red.*
- *→ Correct segmentation*

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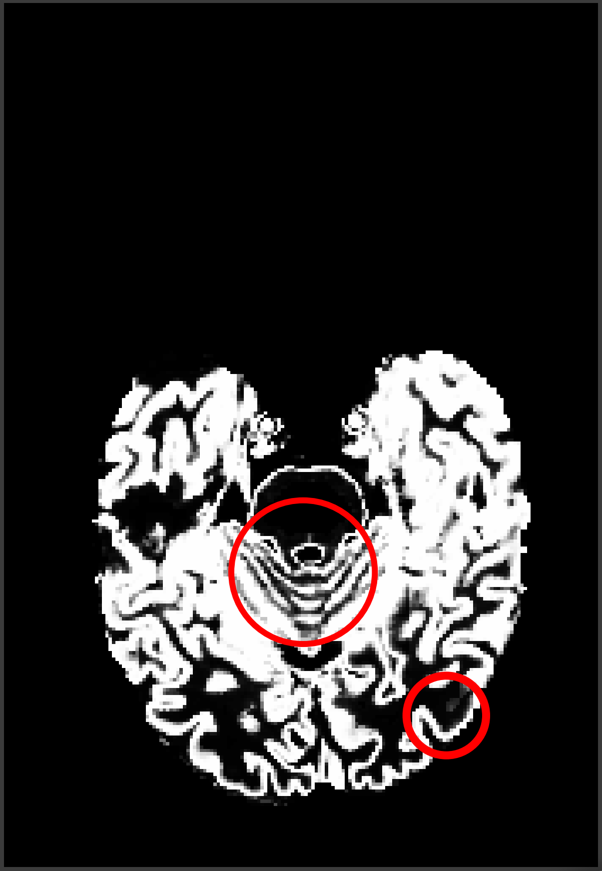
EMS vs. Geo Cuts

EMS gray matter

Geo-Cuts gray matter



Geo-Cuts white matter

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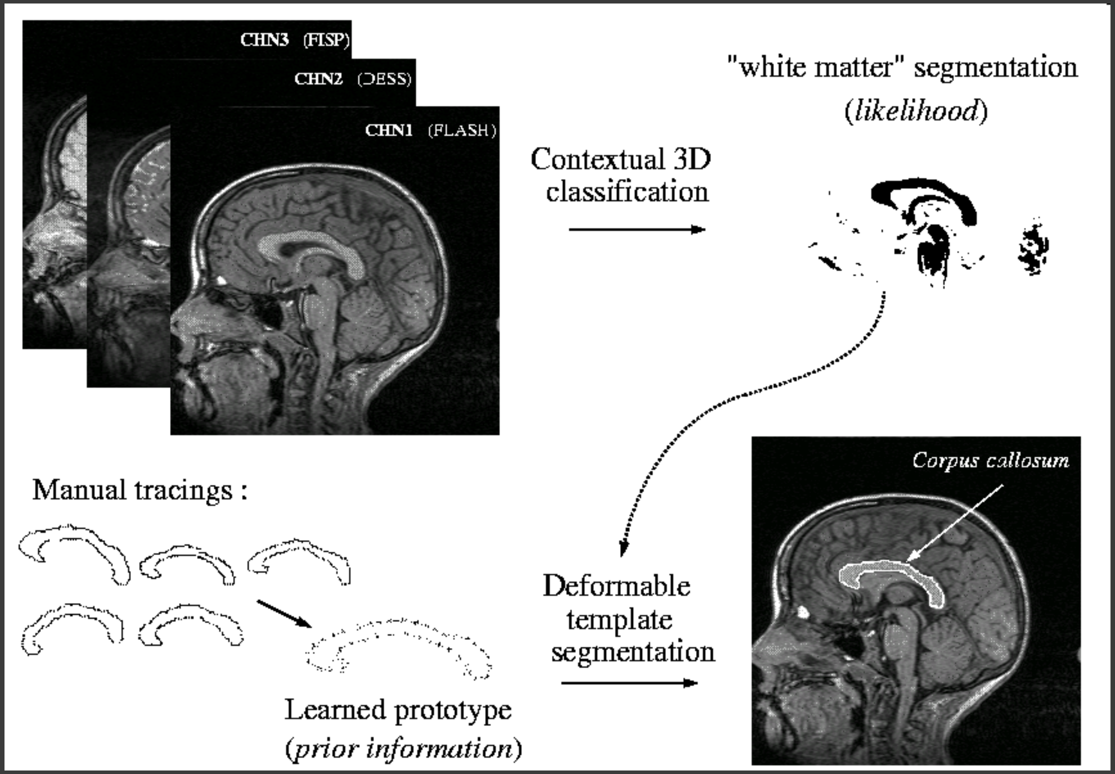
Deformable Models

- So far segmentation methods have not exploited knowledge of shape.
- In shape based methods, the segmentation problem is again formulated as an energy-minimization problem. However, a curve evolves in the image until it reaches the lowest energy state instead of a MRF.
- External and internal forces deform the shape control the evolution of segmentation.

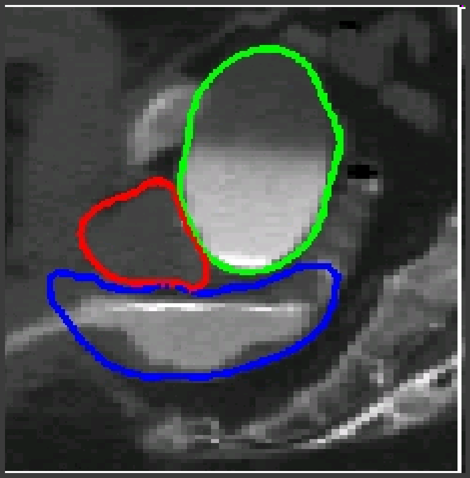
Deformable Template Segmentation

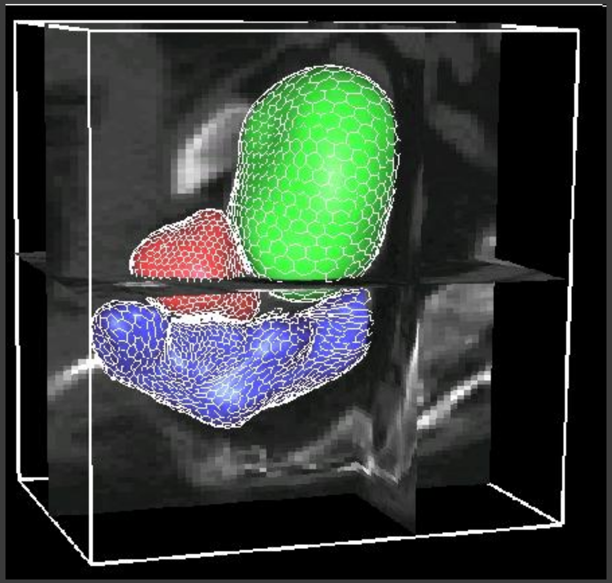


A. Lundervold et al.
Model-guided Segmentation of Corpus Callosum in MR Images
www.uib.no/.../arvid/cvpr99/cvpr99_7pp.html

3D Deformable Surfaces

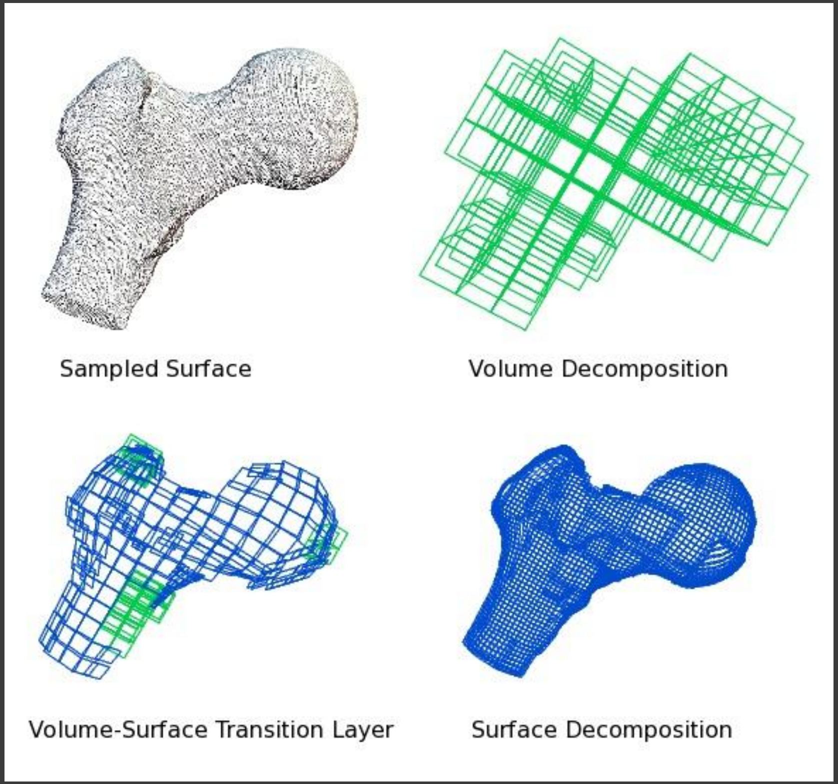
Automated Delineation of Prostate Bladder and Rectum





Costa, J. École Nationale Supérieure des Mines de Paris
www.jimenacosta.com/Jime.Publications.MICCAI0

3D Deformable Surfaces



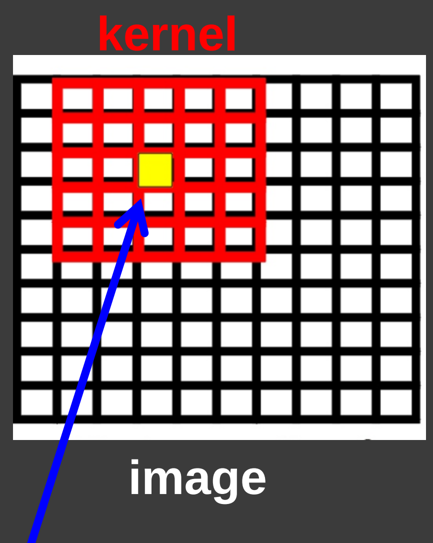
Tamy Boubekeur, Wolfgang Heidrich, Xavier Granier, Christophe Schlick
Computer Graphics Forum (Proceedings of EUROGRAPHICS 2006), Volume 25, Number 3, page 399--406 - 2006

Segmentation Via Texture Extraction

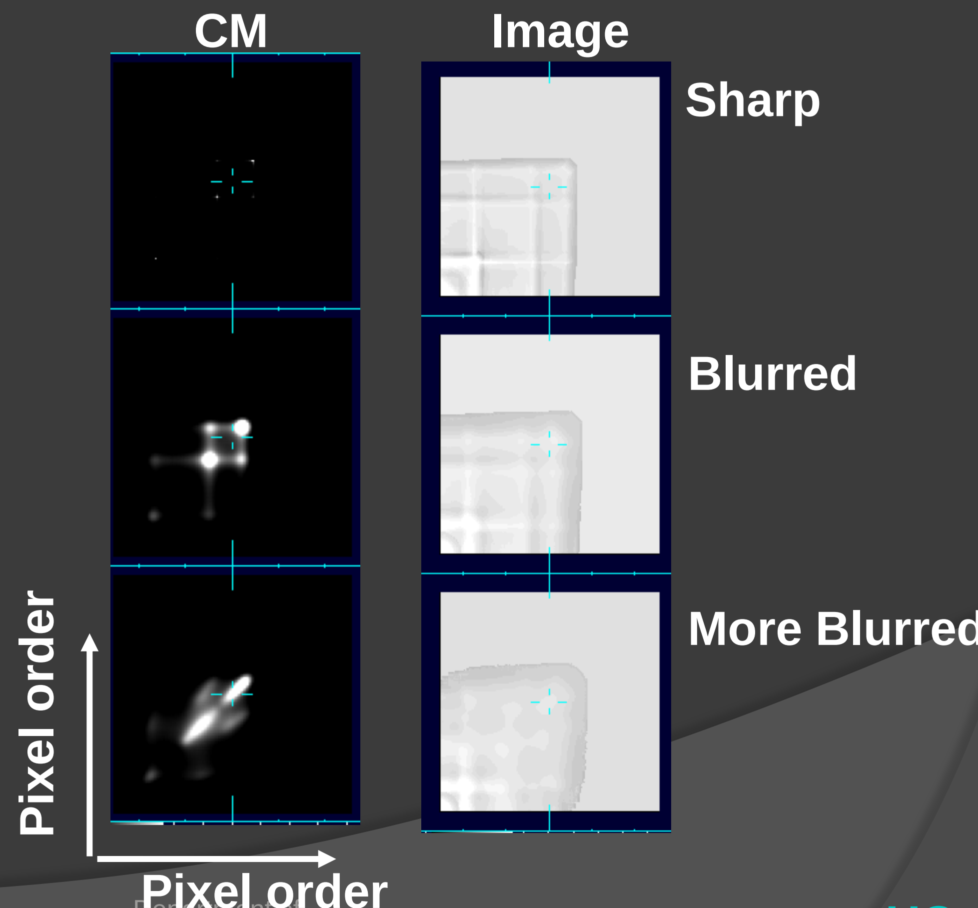
- Two classical methods for feature extraction
  - Co-occurrence matrix (CM)
  - Fractal dimensions (FD)

Co-Occurrance Matrix (CM)

Definition: The CM is a tabulation of how often different combinations of pixel brightness values (gray levels) occur in an image.

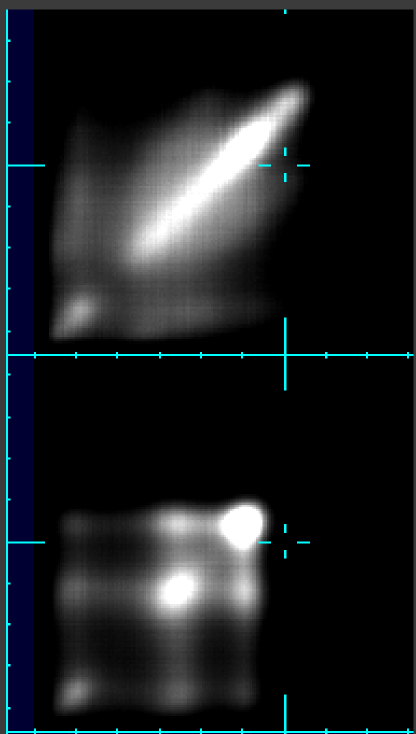


Pixel that stores calculated CM value

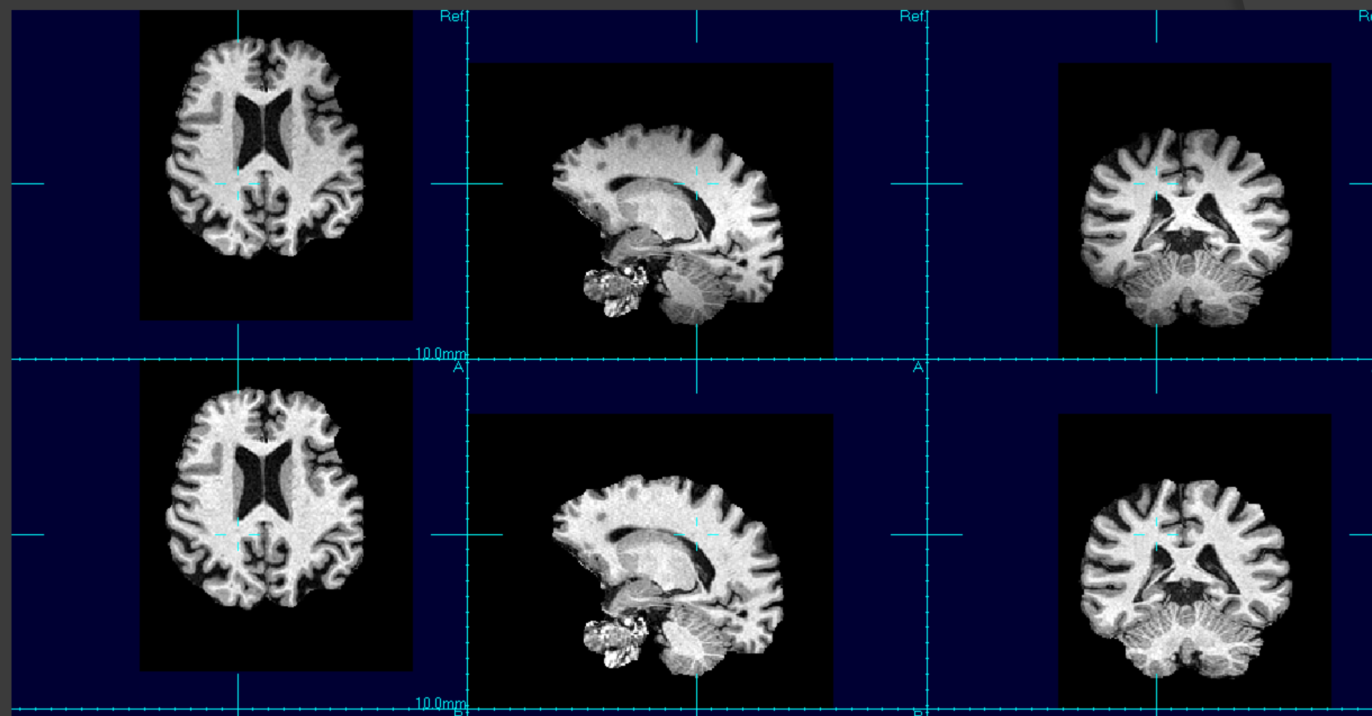


Evaluation of CM

CM



MRI with spatially varying intensity bias



MRI with spatially homogenous intensity bias

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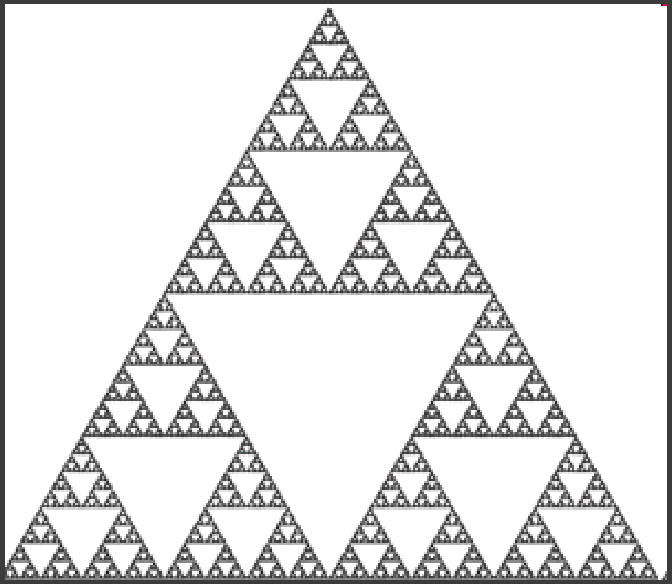
Fractal Dimensions

Intuitive Idea:

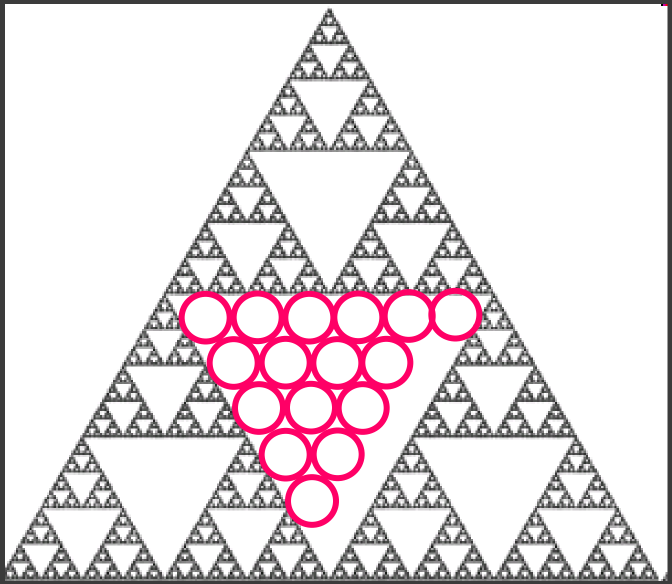
Many natural objects have structures that are repeated regardless of scale. Repetitive structures can be quantified by fractal dimensions (FD).



Sierpinski Triangle

Fractal Dimensions

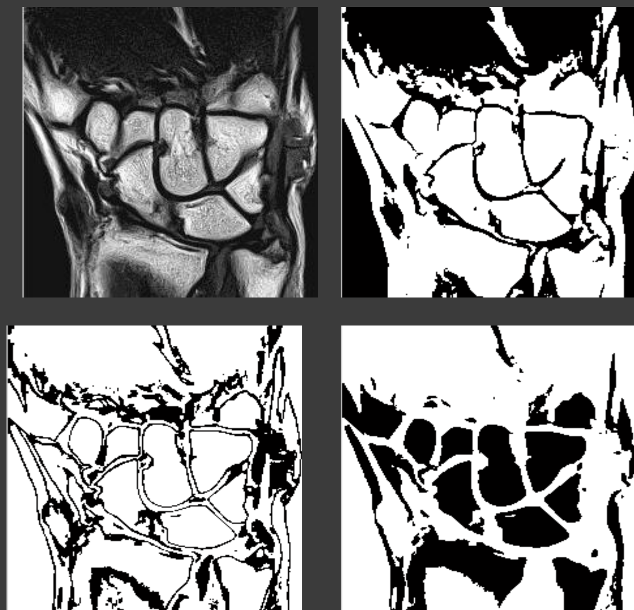
Definition:

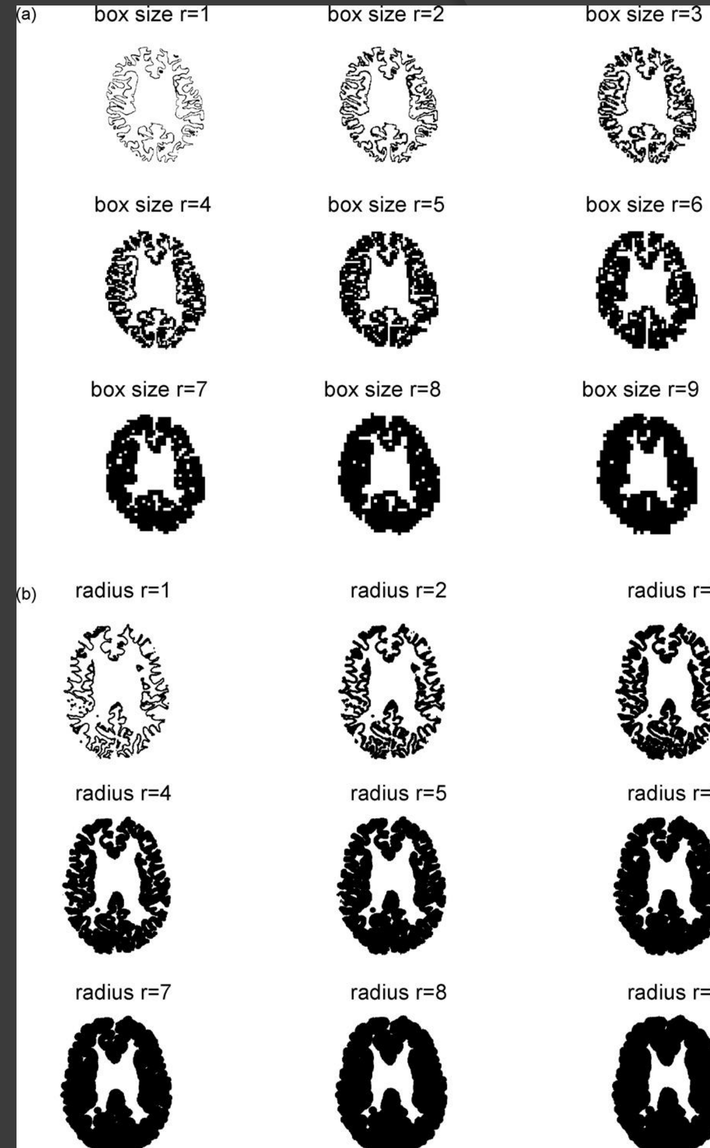


Sierpinski Triangle

Box counting

Fractal Dimensions





MEDICAL IMAGE SEGMENTATION USING MULTIFRACTAL ANALYSIS
Soundararajan Ezekiel;
www.cosc.iup.edu/sezekiel/Publications/Medical

Summary

Automated	Semi-automated	Initializing	Manual
Threshold	Region growing	Co-occurrence	Tracing
MRF	K-means		
Shape Models	Fuzzy C-Means		
Fractal Dimensions			

Literature

1. Segmentation Methods I and II; in Handbook of Biomedical Imaging; Ed. J. S. Suri; Kluwer Academic 2005.
2. WIKI-Books: http://en.wikibooks.org/wiki/SPM-VBM
3. FSL- FAST:http://www.fmrib.ox.ac.uk/fsl/fast4/index.html